Insect Phenology: a geographical perspective

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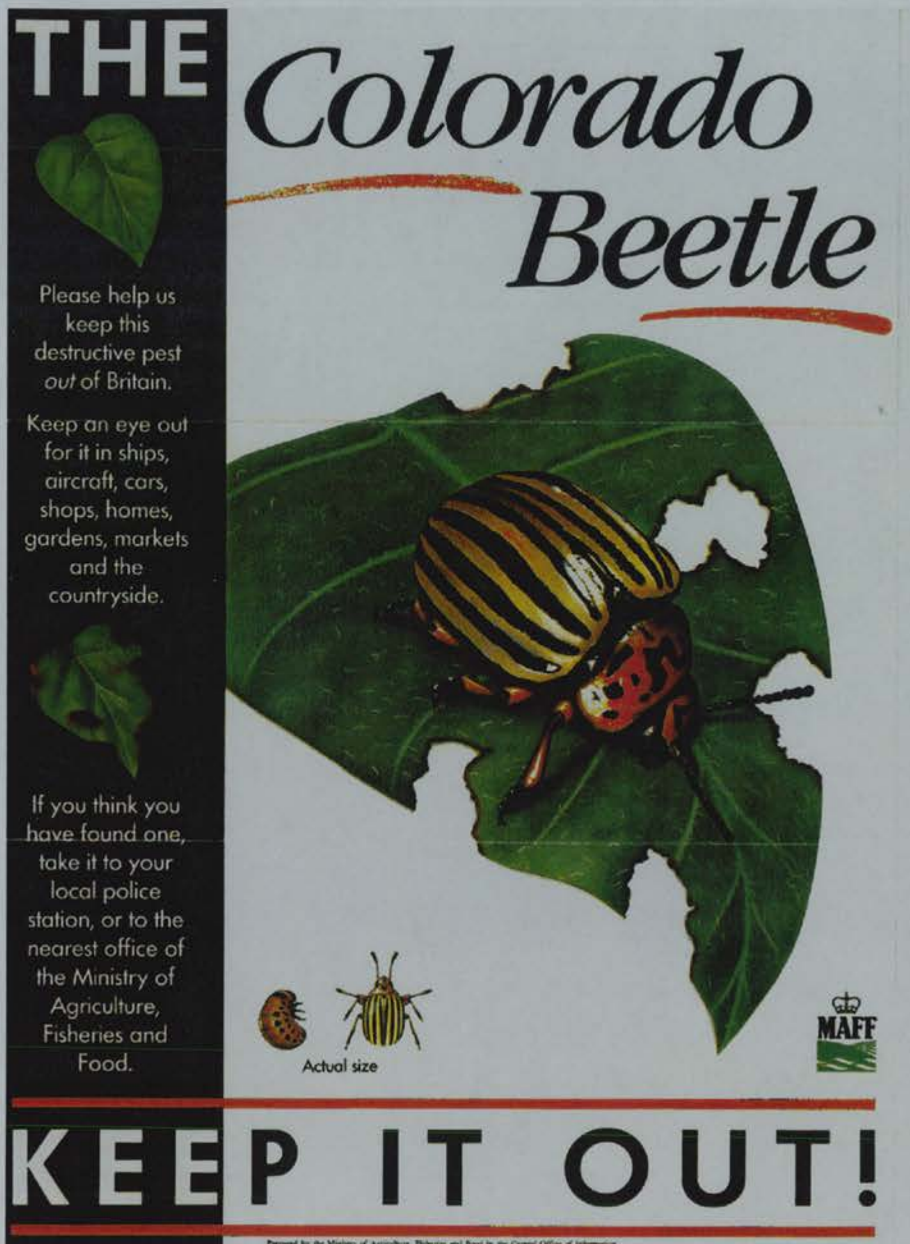

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Declaration

I declare that the work for this thesis has been carried out by me, and where work by others has been incorporated, it has duly been acknowledged and referenced

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Abstract

The rate of insect development (phenology) is strongly associated with temperature. Within the biological literature, phenologies are estimated largely on the basis of sparsely located point meteorological data. The significance of incorporating a geographical dimension was explored in relation to two application areas where phenologies are used, pest risk assessment (PRA) and integrated pest management (IPM). Colorado beetle (*Leptinotarsa decemlineata*) and codling moth (*Cydia pomonella*) were used as representative non-indigenous and indigenous test organisms.

To ensure relevance to both pest risk assessment and integrated pest management applications, phenology models were run using daily meteorological data throughout England and Wales. Interpolation was chosen as an efficient means to create spatial temperature 'surfaces' from distributed daily maximum and minimum temperature data observed at a subset of 174 meteorological stations. Because insect pests are known to be highly sensitive to temperature, considerable attention was paid to minimising the errors generated as part of this process relative to that in previous applied agricultural studies. Comparisons between the commonly used trend surface and inverse distance weighting methods of interpolation were made with partial thin plate splines and ordinary kriging. Unlike earlier work, automatic parameter selection was used to calibrate all the interpolation techniques and care was taken to ensure the comparability of estimated temperature values. Error in estimates by all methods was reduced using a number of guiding topo-climate and land cover covariates. The most favourable estimates of maximum and minimum temperatures throughout the country and over the annual cycle were partial thin plate splines, with daily average r.m.s. accuracies computed using jack-knife cross-validation of 0.8°C and 1.14°C respectively. Partial thin plate splines were also found to be more computationally efficient than both inverse distance weighting and de-trended ordinary kriging. This use of jack-knife cross-validation was assessed using a fully independent data set of a further 100 data points, and was found to be statistically comparable.

Providing the interaction between phenology models and sequences of geographically relevant temperature data at this daily step and national coverage necessitated the construction of tailor made research software for the project. The coupled temperature interpolation/phenology modelling system was used to provide a range of outputs to explore the accuracy of predicted phenologies over space and time. The question was explored whether the interpolation of spatial inputs to a phenology model which is then run multiple times over the landscape provides any advantages over the more computationally efficient, but potentially less physically based, method of running the model over the year and then using one interpolation to distribute the results geographically at the end of the season. This question has rarely been addressed explicitly within a GIScience context previously, despite its potential significance to much applied environmental modelling. Interpolating results of phenology models was found to give rise both to biologically implausible insect development sequences and to over-smoothed surfaces relative to those computed using interpolated input temperatures.

A binary establishment index was developed that allowed the inter-year variability in geographical patterns of pest risk between years (1961-90) to be explored. Comparison between areas at risk generated using point based compared to interpolated results indicated significant differences, both when considering areas of relevant cropland and the overall landscape. Additionally it was found that, on average, the use of interpolated temperatures halved modelling error in predicted timings at all stages of indigenous insect development relative to those computed using data from the nearest meteorological station. Investigation of the spatial pattern of the differences between methods revealed that only rarely did the spline based results perform worse than the nearest neighbour approach, and then only with a small detrimental effect. In contrast, data errors computed using the nearest neighbour method consistently performed poorly. This pattern was found both in lowland agricultural areas and at upland sites.

The few examples of geographical insect phenologies prior to this study were based upon interpolated biological results over limited regions, while previous geographical approaches to pest risk assessment have been based on climate normal data. The implications from this thesis are that interpolated daily temperatures form a preferred base on which to build and extend phenological modelling, and that work is needed to improve the provision of spatially referenced input data to applied biologists. In the context of indigenous pest management, the ability to target control measures more accurately in time and space might for example allow the more effective use of fewer chemical applications or improve environmentally integrated strategies. For pest risk assessment, the results demonstrate the value of using temperature data that does not solely focus on long term averages in order to avoid the masking of extreme but potentially significant risk probabilities. They also suggest that the use of fully spatial phenologies rather than point based figures reduces the possibility of bias owing to variation in geography, which otherwise could be introduced within quarantine negotiations.

Acknowledgements

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My greatest debt is owed to Neil Stuart of the Department of Geography, University of Edinburgh for his good-humoured support, coffee and Kit-Kats throughout the studentship. In particular, his careful editing of much of the first draft of the thesis was appreciated. Also within the Department of Geography, the patient assistance of the computer support crew (Chris, Gavin and Steve) was unstinting while a big thanks too goes to my office mates (Maeve, Mette, Mike, Ulli, Zhu) for their consideration, encouragement and humour. Further afield, Michael Hutchinson generously gave me permission to use and alter his partial thin plate spline code for the purpose of PhD study while much was learned on the geostatistical front from Hans Wackernagel and Dan Cornford while at an EU seminar in Volterra, Italy.

Finally, to friends and family who have consistently supported me, especially through times of illness, many, many thanks.

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Glossary

Accumulated temperature	Integrated excess or deficiency of temperature about a fixed datum (Hallett and Jones, 1993)
Adiabatic	Type of process in which the overall energy of a system is maintained, necessitating changes of temperature with changes in pressure
Albedo	A measure of the reflectivity of any surface in response to solar radiation (Wheeler and Mayes 1997)
Bias	The sum of the difference between the expected value of the estimator and the true value over all samples (i.e. average)
Biofix	Biologically distinctive point during an insect lifecycle used to calibrate models
Bootstrap	Data re-use method for estimating an error distribution, involving the elimination of multiple sample points at any one time
Climate normal	Long term average climate (usually over 30 years, averaged to the nearest decade i.e. currently 1961-90)
Degree days	Accumulate temperatures over a particular base (^{o}C)
Developmental threshold	Minimum value of accumulated temperature below which no development takes place
Diapause	A physiological state of arrested metabolism, growth and development that occurs at one stage of the lifecycle (Pedigo 1996).
Ecdysis	The process of shedding the old cuticle
Entomology	The study of insects
Fecundity	Egg laying ability (rate) of females
Frost hollow	A valley floor area into which cold air will drain by the motion of katabatic winds (Wheeler and Mayes 1997)
Instar	The insect between molts (Pedigo 1996)
Integrated pest management	A comprehensive approach to dealing with pests that strives to reduce pest status to tolerable levels by using methods that are effective, economically sound and ecologically compatible (Pedigo 1996)
Insect ecology	The study of insects in relation to their environment
Jack-knife	Data re-use method for estimating an error distribution, involving the systematic deletion of each datum, estimating its value, and then reinserting it.
Katabatic wind	A local wind caused when the loss of heat from air in contact with the cooling land surface causes it to become denser and be displaced downslope (Wheeler and Mayes 1997)

Lapse rate	The decrease of temperature with increased elevation as a result of adiabatic cooling (Linacre 1992, p73). 'Standard' average rate usually approximated to 6°C/1000m
Oviposition	The act of egg laying (Pedigo 1996)
Pest risk analysis	Identification, assessment and management of non indigenous species
Pest risk assessment	Assessment phase of pest risk analysis
Phenology	The periodicity of biological phenomena (Pedigo 1996)
Photoperiod	Day length
Poikilothermic	Having body temperatures that fluctuate with environmental temperatures, cold blooded.
Polyphagous	Feeding on many types of food
Quarantine pests	Pests of economic importance to an area endangered but not yet present, or present but not widely or commonly distributed and being officially controlled (Hopper 1991).
Residual	The difference between the actual value and estimated value (actual – estimated)
Standard exposure (UKMO)	Standardised conditions for the siting and measurement of climate variables to allow comparability of readings. UKMO recommend instruments be placed in a white slatted screen 1.5m from the ground, in a flat and exposed situation
Target event	Term introduced by Schaub (1995b) to represent a particular modelling output goal e.g. date at which a particular stage of development is reached or percentage emergence on a specified date , now widely adopted (e.g. Régnière 1996)
Thermal constant	The number of degree days required for an event (e.g. pupation) to occur.
Weather generator	Stochastic simulation of weather on the basis of long term climate statistics

Acronyms

CLIMEX	Climate matching software for insect pest applications (Skarratt *et al.* 1995)
DD	Degree days
DESSAC	Decision Support System for Agriculture (Brooks, 1998)
DSS	Decision Support System
EPPO	European Plant Protection Organisation
GCV	Generalised cross-validation
GIS	Geographical Information System
GIScience	Geographical Information Science
IDW	Inverse distance weighted interpolation
IPM	Integrated pest management
IPPC	International Plant Protection Convention
OCV	Ordinary cross-validation
PRA	Pest risk assessment
r.m.s. (error)	Root mean square (error)
UKMO	United Kingdom Meteorological Office

1 Introduction

1.0 Introduction

This thesis focuses on the geographical variations of insect development in the context of an ongoing requirement for farmers to manage agricultural pest populations in a way that is both environmentally and economically sustainable. After feedstuff and fertiliser, pesticides were the largest component of British farmers' agricultural expenditure on external inputs for 1996 (MAFF, 1996). This highlights the economic significance of the topic. Additionally, means of controlling pests bring with them agricultural and environmental problems, from pollution by chemical compounds to the potential hazards to ecosystem equilibrium posed by biological methods of control. The work touches both on the manner in which the threat posed by non-indigenous pests is assessed (*pest risk assessment*) and the scope for the better targeting of control actions in the case of indigenous pests (*integrated pest management*).

The underlying rationale behind this thesis is that geography provides a means to understand more fully the environmental influences upon individual biological processes. Many individual components of the overall crop control system are important fields of research in their own right, for example the biology of pest development and movement and the chemistry of pesticide pollution. A geographical framework provides a means of integrating these research efforts through the commonality of location in time and space. Such an integrated modelling approach might afford a potentially more sustainable agriculture, for example by explicitly linking pest models and subsequent suggestions for control measures that take into account environmental sensitivity to chemical leaching or build-up. However, the concept of a more sustainable agricultural system for Britain provides a broad theme rather than a focused goal for a scientific research effort.

As Kareiva (1990) observes, '*Simply saying that the spatial environment is important is to mouth a platitude: what we need to know is whether this presumed importance amounts to much in natural systems*'. The particular goal of this thesis is, in response to this comment, to contribute to knowledge in the field of insect ecology by developing and exploring a computerised view of how a pest's rate of development (*phenology*) varies over space and time. The research methods that are used within this thesis extend the present state of the art in methods for producing continuous estimates of temperatures data across geographical landscapes, and assessing the relative accuracies of the different techniques. Together, these methods allow one to see for the first time what these differences amount to when we seek to assess risk geographically within the agricultural system.

The nature of pest phenology is one of a number of biological concepts that needs to be introduced at this early stage of discussion, given the inter-disciplinary nature of the thesis and the fact that the biological models used within the study predict this characteristic. Importantly, phenology is distinct from the more familiar notions of population. Phenology may be formally defined as the '*periodicity of biological phenomena*' (Pedigo 1996, p648), and has long been a subject of interest to natural historians. Its focus is upon estimating the *timing* of events within a pest's lifecycle, rather than the absolute population. Population estimates are required to determine probable levels of crop damage and economic impact scenarios. However, reliable and comprehensive population models are rarely available. Even for native species these present an important area of current research since the number of factors combining to influence population numbers, both directly and indirectly, are many (Pedigo 1996, p184). Experienced researchers such as Leibhold (1993), who have championed spatial considerations within applied insect ecology, concur that population adds considerable complexity, for which biological knowledge may be unable to sustain environmental modelling possibilities. Unlike predictions of insect population dynamics, insect pest phenology depends primarily on one major variable: temperature (Pedigo 1996, p195). Because the number of driving factors are limited and better understood, relatively reliable phenological models exist for a variety of pests and even in their absence simple temperature budget models may also be used as an indicator of the timing of development and therefore of potential survival.

The use of phenological knowledge is encountered in a large number of agricultural contexts. Discussion within this thesis focuses upon the use of phenology models of agricultural insect pests, whose distribution is relatively unlimited in terms of habitat and on which the impact of natural enemies is less significant in comparison to threatened insect species. The work investigates the potential contribution of a geographical approach to phenology in two application areas, the development of pest risk assessment strategies (non-indigenous pests) and integrated pest management strategies (indigenous pests). These two subject areas are outlined in the following sections. This is followed by a brief review of the research issues in geographical information science that need to be tackled in order to explore such phenologies from a geographical perspective. A glossary is provided to assist with other biological terminology used within the thesis.

1.1 Pest risk assessment

Royer and Yang (1991) define pest risk analysis as *'the estimation of the likelihood of entry of a pest into an area in which it is not wanted, and the potential impact if the pest became established in that area'*. With increased trade in plant material between European countries and beyond, this is a continuing need. It is no longer acceptable for a national authority to impose unilateral sanctions against what van Halteren (1996) terms 'political' pests, as has historically been the case. This implies an increased need for the development of objective scientific techniques to assist with all phases of the pest risk analysis process (identification, assessment and management). Given the focus on applications of geographical phenologies within this thesis, this study focuses on the *assessment* phase of pest risk analysis, and in particular the likelihood of a pest becoming established throughout the country after arrival on the basis of the temperature available during its developmental period. Other areas of the overall task that is pest risk assessment are also potentially suited to geographical analysis, for example the investigation of the probability of a pest's initial importation or estimating the likelihood of an establishing species spreading over time. However, these subjects sit less comfortably with the phenological approach adopted within this thesis.

Since the development of insect pests is largely governed by temperature, a common starting point in pest risk assessments is to investigate whether local climate provides conditions under which a particular non-indigenous pest has the potential to thrive. Perhaps the most widely known tool for investigating this issue is a system known as CLIMEX (Skarratt *et al.* 1995), a tool with strong similarities to BIOCLIM (Booth 1988) and the more recent GARP (Stockwell and Peters, 1999). While CLIMEX with its climate matching and mapping facility is a dominant tool within the recent literature for determining the establishment potential of non-indigenous pests, there are those who prefer alternative eco-climatic approaches. In either form, results are commonly presented as *point data*, confined to the location of known meteorological recording sites. In a growing minority of cases, gridded rather than point based climate normals have been used within pest risk assessments to present a fuller picture of establishment potential (e.g. Baker *et al.* 1996, Baufeld *et al.* 1996). However, differences arising as a result of using a geographical or fully spatial approach, rather than the point based method, have not been investigated. Additionally, while digital crop data have been used to assist with the visualisation of risk (Braasch *et al.*, 1996), they have rarely been used to enhance quantitative assessments. Both issues will be explored for the first time within this thesis.

In addition to their limited spatial portrayal, insect pest risk assessments to date have most commonly been based upon *monthly* aggregated climate indicators rather than the daily records more commonly used when modelling indigenous pests. Given the short length of lifecycle of many insects, this raises considerable problems of temporal scale. Furthermore, conclusions are drawn on the basis of monthly, seasonal (winter/summer) or annual climate normals. This may result in obscuring the annual variation in risk posed, despite the fact that within risk analyses as a whole it is often extreme events that hold greatest significance. An isolated study assessing the risks posed by fireblight (a disease of horticultural significance) to Australia as a result of trade with nearby New Zealand (Roberts 1991) demonstrates the possibility that deductively derived process models working on a daily time step may be available for more commonly established pests and could be used in PRA. This work will explore how the use of such models and data of finer temporal granularity may impact upon the overall assessment.

1.2 Integrated pest management

The management of *indigenous crop pests* has always been an issue for the farming community, the mainstay of the fight against invasion over the past 50 years being the use of pesticides. This 'technological' solution intensified in step with other farming practices to the degree that prophylactic spraying on dates pre-determined by manufacturers was a standard 'risk minimisation' approach. Both inter-year and regional variations in pest development were ignored. However, the resultant increase in resistance to pesticides (Roush and Tabashnik, 1990) together with the growing environmental awareness of consumers (Cuperus *et al.* 1996, Bromilow *et al.* 1998) has meant that UK policy on pesticides is now to promote their 'responsible' use. Ward (1995) characterises this shift as part of a 'post-productivist' movement, in which production interests are becoming subsumed by consumer interests as political power shifts and budgetary considerations move towards the preservation of rural local communities rather than large scale, over producing high tech. agricultural enterprise. From both these environmental and productivist viewpoints has come the wider adoption of the principle of integrated pest management (IPM).

IPM is an evolving phrase, but has been described as *'the reduction of pest problems by actions selected after the life systems of the pests are understood and the ecological as well as the economic consequences of these actions have been predicted, as accurately as possible, to be in the best interest of mankind.'* (Van Emden and Peakall, 1996, p39). The term integrated implies the combined use of a wider range of more focused techniques to manage pest risk, for example the use of biological and cultural controls or the timed introduction of natural enemies, but does not exclude the use of pesticides. Within this context pesticides remain, perhaps until the introduction of economic incentives to the contrary, an important component of the pest management equation, but are '*increasingly used as a stiletto instead of a scythe*' (Van Emden and Peakall, 1996, p4) through careful targeting in time. Issues regarding the improved precision in the timing of applications of more recent 'greener' botanical agents are similar if not more critical to those of pesticides owing to their shorter persistence and higher product cost (Blago and de Barardinis, 1991). Understanding an insect's phenology plays a direct role in this newer approach to pest risk management and control.

Knowledge of the time at which pests may reach certain developmental stages according to local conditions may be applied to assist with the monitoring, sampling and timing of treatment. Modern pesticides have a limited effectiveness over time. They are often developed for specific stages of the insect life cycle: most commonly the larval stage. To be most effective, treatment should be timed to reach the maximum possible number of pests in one application. This is exactly the type of information given by phenology models that commonly report the proportion of a population reaching given developmental stages through time. Without such models, the timing for treatment must be determined from potentially time-consuming field monitoring. The decision of *whether* as opposed to *when* to spray is, in the absence of reliable population models, determined by field sampling followed by the application of economic analysis. The relative timing of different pests and their natural predators, or between pests and crop planting, is also used to assist in determining spraying or biological control schedules (Van Emden and Peakall 1996 p79, Mills and Getz 1996). Phenology models are however critically dependent on temperature data, which may not be available locally. This suggests that while considerable effort has been placed on the sharper targeting of combinations of control techniques in the temporal domain, there is scope to improve management practices further (using existing biological models) if they can be placed within a context of both space *and* time through the provision of more locally relevant input temperature data.

The degree to which the use of phenology models in practice is compromised by non-local input data remains little researched to date. Work by Finch *et al.* (1996) typifies the current use of phenology models within the UK horticultural industry, where advice regarding critical development times is being given on the basis of data at regional meteorological stations only. Limitations to the current point based approach are evident when estimates, limited spatially by a lack of real-time agro-meteorological data which drive the underlying models, are mapped (e.g. Parker and Turner 1996). The use of on-farm weather stations is growing in Britain as in Europe (e.g. Høstgaard 1994) to fill this gap, but multi-sensor equipment is expensive and requires investment in downloading time. In the minority of papers reporting geographical phenologies, these have been constructed through the interpolation of phenological model results. This contrasts with the route taken within this study, which is to focus on the provision of spatially referenced input data that might be used to support current British agricultural decision support system (DSS) initiatives (e.g. DESSAC, Brooks 1998 and MORPH, Walton 1998).

This work will explore the possibilities of driving insect phenology models using spatially distributed model input data. Improved results will support the case for improved spatial agro-meteorological data provision to complement and capitalise upon biological research efforts. Moreover, findings of significant increases in accuracy when estimating phenology over time using the geographical (fully spatial) approach would strengthen the case for using spatial decision support systems (SDSS) to improve the uptake of integrated pest management practices.

1.3 Geographical research context

So far, this introduction has outlined the application area for this study, with the aim of identifying the gaps in the geographies of pest risk developed to date and establishing the case for exploring pest phenologies in space and time. Many of the geographical themes addressed within the project (Figure 1-1) link with broader issues in geographical information science and environmental modelling research. By focusing initially on the end requirements, the intention is to allow the application to lead the scope of geographical work. Previous studies in this research area, largely carried out by biologists, have tended to allow the present state of geographical science and technology to constrain the possibilities. From a geographer's perspective, there is an equal danger of developing complex theoretical GIS strategies to model insect behaviour that cannot be correctly parameterised and tested in practice owing to limitations in the current state of biological knowledge.

The basic theme in this work from a biological research perspective is to provide a spatial dimension to the phenology model results that is currently lacking in the point based predictions in common use, and to analyse the potential implications of the geographical results. Providing predictions of pest risk not just at sparsely located points but continuously over the landscape of England and Wales creates many opportunities and challenges within the GIScience arena, to which Figure 1-1 refers.

Climate variables, required to drive insect phenology models, are incorporated within many environmental models within hydrological (e.g. Hay *et al.* 1996) and crop modelling (Landau *et al.* 1998, Supit 1997) domains. Both geostatistical techniques and process-based circulation models are commonly used to provide spatially continuous temperature surfaces (e.g. Running and Thornton 1996, Pielke *et al.* 1996, Hutchinson 1991a, Cornford 1997). Much of the published literature however relates to the interpolation of monthly climate data (e.g. Hutchinson 1991b, Lennon and Turner 1995), rather than daily data as required in this case. Where the focus is upon daily data at fine resolutions, the modelling extent is predominantly regional or local (Running and Thornton 1996). In meteorological terms, it has been suggested that the largest gap in our knowledge of the thermal environment lies in '*understanding the changes in parameters, variables and functional relationships at the intermediate scale (10m up to 10km)*' (Carlson *et al.*, 1995): the very interval required for this pest risk modelling study. Additionally, it is still the case that few examples of geographical modelling attempt national coverage, at such grid resolutions. The work of Lennon and Turner (1995), albeit regarding monthly temperatures, points a way forward to an efficient solution to the continuous surface problem through a combination of topoclimatic and geostatistical approaches. This is echoed at a daily time step by Cornford (1997), who combined a range of topoclimatic indices and ordinary kriging to produce minimum winter temperature surfaces for England and Wales.

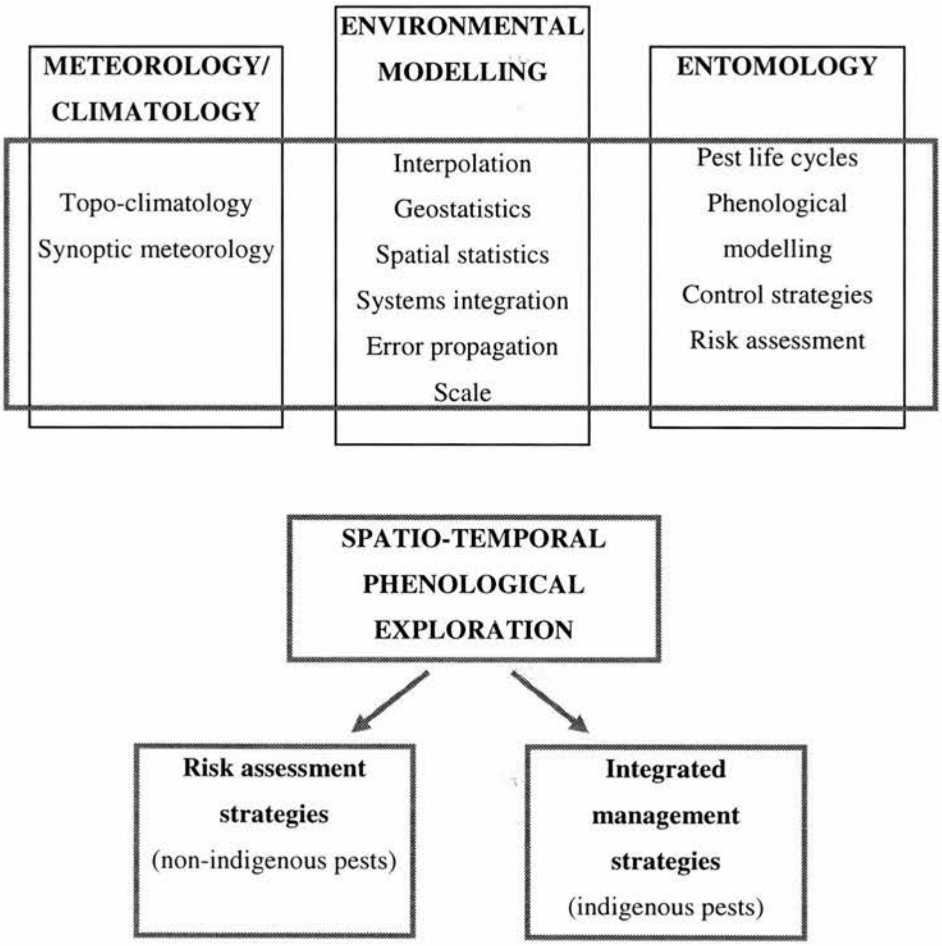

Figure 1-1 Research areas relating to this study

A variety of methods have been used to construct continuous surfaces of climate variables in the climatological literature, where these surfaces are commonly considered the goal of particular studies. However, few *applied* studies which use these continuous data as driving inputs have incorporated the more sophisticated interpolation algorithms available (e.g. Supit *et al.* 1998) or the range of potential topoclimatic variables that could be considered (e.g. Landau and Barnett, 1996). It is rare that input error is propagated through models running over annual time sequences at different locations in space to provide a measure of the effect of such decisions regarding input data. Indeed, more often than not, it is the outputs of temperature driven models that are interpolated to produce continuous outputs, rather than the driving variables themselves. The merits of these two quite different approaches to modelling have been little explored, particularly within a GIScience setting.

The means by which process models may be integrated with GIS forms a further important strand within the GIScience research literature, to which consideration must be given within the thesis. As Maidment (1993) observed, divisions between research groups may be drawn according to whether it is considered that environmental modelling can be carried out within an extended GIS environment (e.g. Van Deursen 1995, Wesseling *et al.* 1996) or whether a focus should be placed on improved data structures (Abel *et al.* 1992, Kemp 1997a,b, Raper 1999) or interoperability between systems (OGC 1996).

1.4 Study context

This work has been undertaken in conjunction with MAFF Central Science Laboratory, a government agency charged with the mission '*to use science to help safeguard the supply of food and to protect the environment and the consumer*' (http://www/csl.gov.uk). Part of CSL's remit is its requirement to assist in protecting plants from pests, both in terms of developing a better scientific understanding of plant-pest interactions and also practical strategies for targeting preventative action. This collaboration provides distinct advantages for this study such as biological expertise, social relevance and accountability. In turn however, it also lends a certain degree of institutional context to the overall project direction.

Figure 1-2 illustrates typical levels of decision making within an organisation. The overall aims for CSL reflect this variety of decision support needs, from preventative action over short time scales in local areas (integrated pest management) up to the development of international policy on the basis of pest risk assessments. Research to address all such aspects is not feasible within one thesis. The prototype system will examine scientific questions regarding the spatio-temporal aspects of insect phenologies at the management level, reflecting the goal of building a framework useful for further analysis at a variety of spatial and temporal scales. This choice reflects a balance between innovation, application and the availability of data. At a national level for example, climate modelling and meteorological provision is currently made at scales between $40km^2$ and $10km^2$ and this work aims to model to $1km^2$, reflecting a considerable advance in detail. In terms of the variability in insect

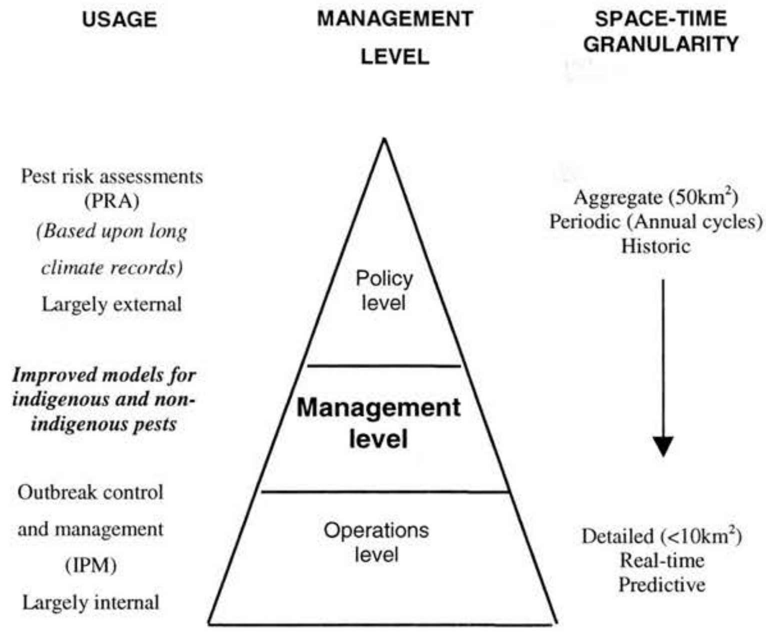

Figure 1-2. Range of requirements for decision support in crop pest management

development however, these scales are still coarse. The density of data in the UK national synoptic network sets a lower limit to the resolution of modelling, whereas greater detail might be achieved in local regions by using additional field sensors. The primary pest risk assessment application allows *relative* comparisons between years. This includes scope for techniques to be incorporated that may be useful in exploring further environmental variables as required, and for other models to be substituted. The framework developed is also intended as a tool that could support the exploration of specific biological hypotheses in addition to more pragmatic pest management aims.

Research contributing to applications needs to be developed with a target user in mind. In the future, interpolated input data and modelled spatial phenologies for extensive areas will be incorporated within horticultural/agricultural information systems designed specifically for the farming community like DESSAC or MORPH. However, this prototype is aimed at supporting computer literate, expert biological users to address basic scientific questions from which it is hoped that management implications and focused on-farm systems will later follow. While an interactive user interface would assist the biological researchers in *exploring* results within this environment it is not critical to *obtaining* them. Developing a sophisticated user interface, and focusing on system performance, were therefore not considered priorities within this work.

1.5 Aim and objectives

Within this context of the agricultural/horticultural needs for improved risk assessments, and particularly for more precise information on where a pest may thrive in time and space, the specific aim of the thesis is:

- to build a prototype system capable of modelling insect phenology through both time and space throughout mainland England and Wales at a grid resolution that is appropriate for assessing the consequent risk to crops, and explore the time and geography of the resultant phenologies.

In meeting this aim a number of scientific questions arise:

Basic science

- How may the primary inputs to phenological models, the observations at meteorological stations of daily maximum and minimum temperatures, be estimated continuously over extensive and diverse areas?
- To what extent does the choice among methods of interpolation produce differences in the magnitude and distribution of the input conditions for modelling?
- How does the spatial location of the available meteorological data through the validity of the interpolators used affect the magnitude and distribution of uncertainties in the nation-wide estimation procedures?

Exploration

- Does the fully spatial method reveal significant differences in estimating the timing of risk in comparison with the traditional nearest point method?
- What difference does interpolating phenological model results or phenological model inputs make to the magnitude, distribution and timing of the areas estimated to be at risk?
- How does the time at which insects reach a certain stage in phenological development vary over space and time throughout the calendar year, and between years?

Assessment

- What difference does adopting a geographical (fully spatial) approach make to quantitative assessments of risk for non-native pests?
- How may we best assess the reliability of the resultant spatial phenologies?

Implementation

- Are existing data networks sufficient for this fully spatial approach?
- Can the system be based upon a conventional GIS, or is an alternative structure required?
- Is the science and technology of geographical information handling sufficiently developed to support the creation of operational systems for pest risk assessment?

1.6 Approach

This study follows an experimental approach, in the first part comparing and refining a series of methods and in the second part drawing on practical needs within PRA and IPM to assess the importance of the findings. While its treatment of climatology within the study is empirical, the phenological perspective in contrast draws upon established biological models rather than being data driven. The geographical bounds of the study cover mainland England and Wales, since a national perspective is of crucial importance when assessing the threat posed by non-indigenous pests in particular. The aim is to augment the state of knowledge in GIScience through this work by asking where, and how reliably, can we estimate if and when a pest can thrive.

In order to constrain the scope of the work, two representative insects have been selected for study. Colorado beetle (*Leptinotarsa decemlineata*) is used throughout the thesis in discussions of pest risk assessment as an example of a pest that is not established within Britain, but that poses a considerable threat to British agriculture. Codling moth (*Cydia pomonella*), in contrast, is used to exemplify a typical indigenous pest for which control strategies are required on an on-going basis within the British horticultural industry. Given the focus within the work upon modelling the geographical variations of insect ecology rather than the underlying biology, existing well-parameterised biological models selected by experts in their field for this purpose are used throughout the study. Biological models for Colorado beetle and codling moth, together with the more generic accumulated temperature approach, have been chosen by experts in their field to characterise typical applied biological models in use, and their further refinement falls outside the scope of this thesis.

The core approach within the thesis is the linking of spatially referenced input data (interpolated daily maximum and minimum temperatures) with *phenological* models commonly run at sparse point locations only, since as discussed earlier, reliable population models are rarely available. Given the high sensitivity of insects to temperature, attention to detail when interpolating input temperature data forms an important strand within this work. For estimating the continuous surfaces of input variables to the models, interpolation is chosen in preference to process-based atmospheric modelling for the efficiency of technique, given the data available to the study and the multiple climate surfaces required. The intention to model daily rather than monthly temperatures raises issues regarding how best to incorporate knowledge of synoptic rather than climate processes over space in order to provide appropriate input data to the biological models. The availability of digital terrain models and GIS enables the exploration of a wider consideration of topo-climatic factors to guide interpolation as one strategy by which results may be improved beyond those of the current literature. Following from this, the extent to which the choice among methods of interpolation produce differences in the magnitude and distribution of the input conditions for modelling is a further issue for research. As a second strategy therefore, more sophisticated interpolation algorithms than those commonly found in applied work are used, and the pay-off between incorporating additional topo-climatic variables and more complex interpolation strategies is also investigated.

Understanding the nature of input error propagating through such a multi-temporal spatially referenced system in relation to the sensitivities of the models has been the subject of little debate either within the spatial phenology or geographical science literature. From a validation perspective, it is also of interest to investigate how the spatial location of the available meteorological data affects the magnitude and distribution of uncertainties in the nation-wide estimation procedure. A comparative approach to experimental design when assessing these geographical and temporal issues is largely followed within this study, in part owing to a lack of independent biological data with which to validate the phenologies. Indeed, the very nature of pest risk assessment, together with the need for confidentiality of previous reports to government makes this inevitable. Care is taken when interpolating to validate results on similar bases between experiments and techniques to this end.

The implementation of this approach requires a further set of more pragmatic issues to be considered. Owing to the nature of the phenological problems under study, a suite of specialised software routines is constructed, to achieve results beyond the capabilities of proprietary GIS. The system itself is a by-product of this research effort, with the principal outcome of the thesis being the new knowledge and understanding gained about the geographical dimension to insect phenology. The work draws draw on similarities in the underlying modelling of phenologies between indigenous and non-indigenous pests to construct geographical phenologies relevant both for applications in pest risk assessment and integrated pest management. Error in the modelled phenologies that results from the use of spatially continuous inputs versus remote point data is also reported. In addition to developing the software framework itself, examination of the sufficiency of the existing data networks will be undertaken through variogram analyses of the temperature data and an examination of the ability with which the interpolation methods could be parameterised. Within the thesis, geographical phenologies are primarily constructed by running biological models multiple times using continuous input data, as opposed to the alternative approach taken in previous studies of interpolating point phenological model results. The effect of this approach on the magnitude, distribution and timing of the areas estimated to be at risk is a further strand of research.

Meteorological data are preferentially located at lowland, and often coastal, sites at the expense of upland areas. The inference of this is that aggregate risk assessments based upon point data may be biased in relation to pest development potential over the full landscape. The effect of adopting a geographical (fully spatial) approach make to quantitative assessments of risk for non-native pests is a further topic for investigation. Additionally, previous work using spatial climate normals (e.g. Baufeld *et al.* 1996) has assessed areas at risk in terms of the overall landscape, rather in relation to the target crop data. Since the rationale of PRA is to protect national economic interests, this issue is considered worthy of investigation. Earlier work in pest risk assessment has been based on climate data aggregated prior to modelling (climate normal data) rather than, as in this case, aggregated post-hoc. It is suggested that this may 'dampen down' the assessment of extreme risks, which are often the most damaging when they occur. The time at which insects reach a certain stage in phenological development vary over space both within a calendar year and between years presents a further topic for exploration. The use of phenology models for PRA purposes does however require a certain number of assumptions to be adopted. For example, employing measures of phenology for assessing the likelihood of a pest establishing in this country does however imply a worst case scenario. In particular, this assumes that no other limiting factors, such as unavailability of food or predatory parasites, limit the pest's survival. Furthermore, all model runs will begin with the assumption that diapausing (winter resting) adults are present throughout the landscape at the beginning of each year.

In an integrated pest management context, poor biological results using field data have often been attributed to a lack of locally relevant temperature data: pests are highly sensitive to small differences. Use of well-interpolated spatial input data is likely to reduce these errors, but the degree to which this is likely to be the case and the locations at which maximal benefits will be achieved are currently unknown. Ongoing investment into improving the accuracies of biological models as part of other projects is likely to result in incremental improvements, but the working hypothesis for this thesis is that a dual strategy, that tackles the *two* complementary areas of both model and input data, may in contrast lead to a non-linear improvement in returns.

The work divides naturally into the following sections:

- Input data and processing;
- Spatially continuous estimates of temperature data;
- The linking of phenology models with spatially distributed temperatures;
- Comparison of results and validation of the geographical approach;
- Assessment of the contribution of geographical phenologies to PRA and IPM.

1.7 Organisation of the thesis

The chapters provide an account of the research process to answer the questions posed above (Section 1.5) according to the approach outlined within Section 1.6. From a practical perspective, the writing follows the design, implementation and evaluation of a prototype system for assessing the risk posed to British agriculture by insect pests on the basis of phenology. Chapter 2 begins by describing the two focus pests studied in this thesis and reviewing how their growth is understood to depend on temperature conditions. Studies that have adopted a geographical approach to modelling landscape-wide pest risk are reviewed. Issues from GIScience concerning the coupling of point based environmental models with GIS and the interpolation of spatial data are then discussed, before considering the specific means to interpolate temperature surfaces and to show the uncertainties inherent in these estimates.

Chapter 3 will describe the particular phenology models used within this study, their basic data requirements, the interpolation algorithms used and work on software linkage that was necessary to build an integrated system within which climate data and biological models could be combined. As part of this methodology, the means by which daily maximum and minimum temperatures were modelled in this study will be outlined. One component of this section will be an explanation of how the topo-climatic factors used as guiding variables to improve the process of interpolating temperature were constructed. A further important component of chapter 3 will be a discussion of the validation methods used within the thesis, including an explanation of the use of jack-knife cross-validation for the propagation of errors resulting from remote input data through the phenology models.

Results from the climate interpolations will be presented within Chapter 4, since these results influenced the choice of method used for creating all subsequent temperature surfaces for input to the phenological models explored in later chapters. Chapter 4 will divide into discussion of the effect of including multiple topo-climatic and land cover factors, verification of the automatic parameterisation of interpolator functions, and comparisons between the different interpolation methods used. Interpolation results for daily maximum and minimum temperatures will be assessed through the use of average error figures for temperatures over one year and throughout England and Wales, in addition to the consideration of the spatial and temporal variability of the residuals from modelling.

Within Chapter 5 the focus of discussion will shift to the mapping and analysis of spatial phenologies. The chapter will begin by introducing a variety of phenological outputs resulting from the software framework, and typical outputs for accumulated temperature, Colorado beetle and codling moth will then be presented and interpreted for reference within subsequent chapters. Additionally, the capabilities of the research framework will be compared with previous work on geographical phenologies on issues such as its efficiency of structure and potential broader application.

The second major component of Chapter 5 will be a focus on system validation, using accumulated temperature results. Accuracies computed using jack-knife cross-validation will be assessed both for their average distribution across different base temperatures and on the basis of their spatial variation. Comparison between results in chapters 4 and 5 will allow comparisons between the spatial patterns of error of the accumulated temperatures in relation to those for their underlying daily temperatures. Additionally, using independent data acquired at a late stage within the thesis, jack-knifed cross-validation results will be compared with those achieved using the truly independent sample for both daily temperatures and accumulated temperatures. Finally, the efficacy of the often used practice of interpolating residuals from environmental models to form a continuous 'error surface' will be investigated empirically.

Chapter 6 uses the resulting geographical phenologies from all three types of phenology model incorporated in the study to explore broader issues of spatio-temporal environmental modelling and the propagation or error arising within this study. The merits of two different approaches, of interpolating either the input data to a phenology model, or model results, will be assessed critically. Their relative accuracies across the range of phenology models used in the thesis, each with different characteristics, will be examined.

Chapter 7 will focus on illustrating the practical potential of the geographical phenologies constructed for the thesis both for pest risk assessment and integrated pest management. Current shortcomings in biological practice and consequent opportunities for geographical phenologies that were identified within chapter 2 will be summarised at the start of the sections for each application area to refresh the reader. In the case of Colorado beetle, the representative non-indigenous organism, the benefits of differences between risk estimates based on point data at meteorological sites rather than this fully spatial approach will be explored. Additionally, the merits of the improved temporal scale, which will allow the inter-year variability in risk to be assessed, will be considered. This section also examines how the configuration of input data may influence the generality of the resulting predictions over space and may particularly lead to differences in identifying marginal areas for pest development. The implications of these results for assessment strategies will be discussed.

In the second half of the chapter, models for the indigenous codling moth will be used to determine variations in critical phenological dates over space. The implications of the findings will be discussed in relation to the timing of precisely targeted current pest management practices. This will build the case for improved agro-meteorological data provision in the form of continuous rather than point-based data.

Within the final chapter, the findings will be summarised under the contributions first to GIScience and secondly to an understanding of insect phenology. These will be assessed in terms of how the results match prior assumptions, and through a discussion of strategic improvements that might be made to the modelling approaches taken. Implications for both pest risk assessment and integrated pest management will be summarised. A number of areas are highlighted for future research. Finally, the main conclusions from the work are summarised as answers to the research questions that were posed in section 1.5.

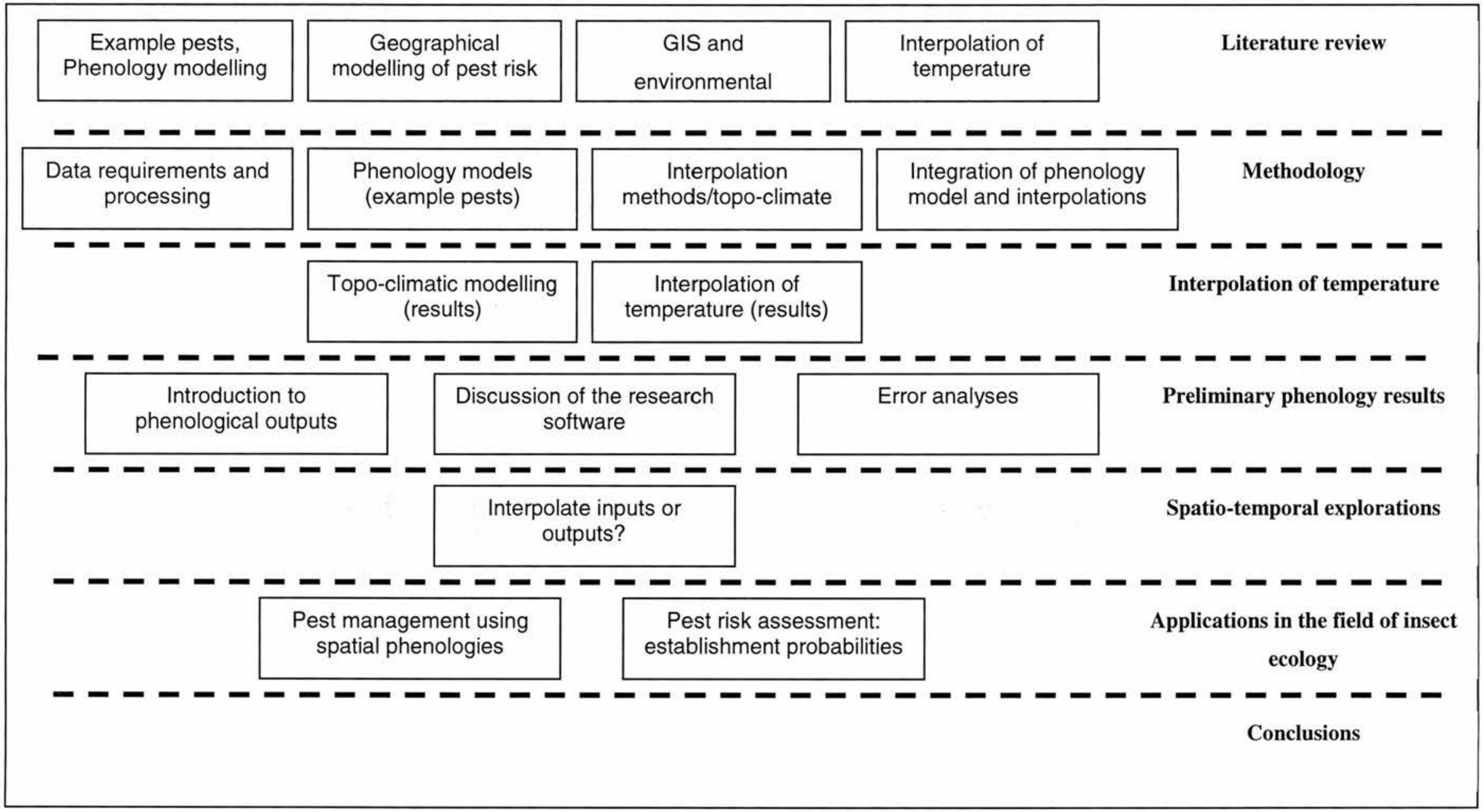

Figure 1-3. Organisation of the thesis

2 Literature review

2.0 Introduction

This chapter reviews the state of research understanding in contributing areas of insect ecology, pest modelling and GIScience. It argues that understanding in all three areas is needed in order to progress the present state of knowledge and to undertake work to provide reliable and relevant information for pest risk assessment and integrated pest management. Sections are subdivided as follows:

- Insect development and pest phenology modelling;
- Geography and insect ecology - past links;
- GIScience issues contributing to environmental modelling.

2.1 Insect development and pest phenology modelling

2.1.1 Life cycles of the focus pests

Insect life cycles vary considerably between species in terms of development phases, times and preferred environment. Those of the two focus pests in this study, the Colorado beetle and the codling moth, are outlined below.

2.1.1.1 Focus pest 1: Colorado Potato Beetle (*Leptinotarsa decemlineata*)

Figure 2-1. Colorado potato beetle larva and adult (From Pedigo, 1996, p187)

Colorado beetle (Figure 2-1) is a serious pest of potatoes throughout mainland Europe (introduced in 1921 per Bartlett 1980). In France, for example, Colorado beetle control is compulsory (Heller *et al.* 1991). As the recent well publicised case at Harwich Docks on 2 August 1997 showed (MAFF Press Release 230/974, August 1997), it is well able to reach and travel within Britain. Indeed, 163 outbreaks have been controlled in the last 50 years although no breeding colony has been formed since 1976 and this was successfully eradicated (Bartlett 1979). The Colorado potato beetle is highly fecund (Harcourt, 1971) in addition to being a voracious defoliator, making early detection vital. Problems of resistance to pesticides are particularly profound for this insect (Casagrande 1987), making the careful application of both currently available pesticides and delta-endotoxins (Rahardja and Whalon 1995) especially crucial. For these reasons it is covered by plant health legislation (Plant Health (Great Britain) Order 1993) as a notifiable quarantine organism. Additionally, related work suggests that climate changes predicted will greatly increase the threat of Colorado beetle to Britain (Baker *et al.* 1996, 1998).

In addition to selecting Colorado beetle owing to its potentially significant economic importance to British agriculture, this particular pest has been chosen in the light of extensive, well documented field studies of its ecology (e.g. Weisz *et al.* 1995, Follet *et al.* 1996, Baker 1991). CSL scientists are among those who have contributed to this understanding with the development of phenological models validated in the Cherbourg peninsula (Baker 1991, Baker and Cohen 1985) and the agency holds a database of over 4,500 research articles on this pest alone. Ongoing collaborative research with European partners will enable the future field verification of the methodology (Baker 1996) otherwise problematic for a non-indigenous pest. This depth of knowledge provides further scope to develop work beyond that achieved within this particular study in the future.

The life cycle of the Colorado beetle is illustrated within Figure 2-2. From this, five developmental phases may be identified: egg, larval, pupal and immature (also termed 'young') adult and mature adult. Its winter resting period (diapause) occurs within the soil environment. Weber and Ferro (1993) have observed a tendency for beetles to over-winter in woody areas adjacent to the fields where they spent their previous summer. Overwintered adults emerge in spring, and may fly several kilometres to find their host habitat if necessary. They then begin feeding and egg laying on small potato, tomato or aubergine plants. Egg masses hatch and small larvae are the predominant life stage, followed by large larvae. Pupation begins, followed by a period when large larvae and 1st generation adults are the predominant life stages. Damage to susceptible crops in the pre-harvest period is indirect: injury is caused when adults and larvae feed on foliage and stems of potato plants, resulting in poor yields at best. Experiments suggest that one adult beetle may consume up to 9.65cm^2 of foliage per day, and 40cm^2 of potato leaves at the larval stage (Ferro *et al.*, 1985). Adults can also be vectors of plant disease (Pedigo 1996, p187).

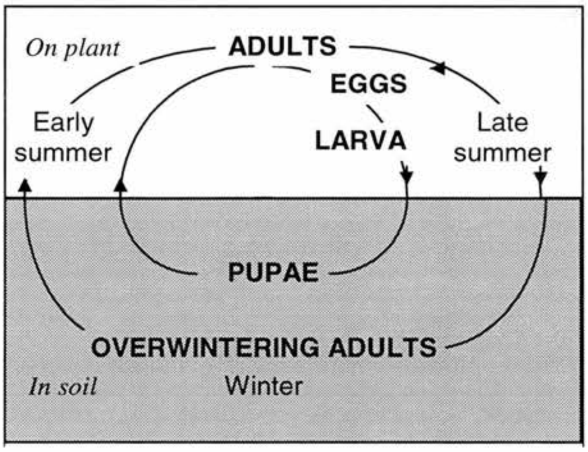

Figure 2-2. Life cycle of Colorado potato beetle (*Leptinotarsa decemlineata*) (Gratwick 1992)

2.1.1.2 Focus pest 2: Codling Moth (*Cydia pomonella*)

The codling moth (Figure 2-3), one of the renowned *Tortricidae* family, is known as one of the most widespread pests of apples, and the British experience is no exception to that in other countries (Hill 1997, p135). It is one of the three major pests encountered by fruit growers in south east England (Morgan and Soloman (1993). The threshold of acceptable damage on these pests is low, since the value of the fruit is highly dependent on its appearance. It is the larvae that are responsible for commercial damage, caused by their burrowing and feeding deep within the fruit as it develops during July and August. Under British conditions, one complete generation of moths per year is the norm, although in warm years a small (5%) second generation of adults may develop in August and September (Gratwick 1992, p108). The fecundity and development rates of the Tortricidae are highly temperature and light sensitive (Morgan 1992), and within warmer areas of Europe and the US multiple generations are the norm (e.g. Pitcairn *et al.* 1992).

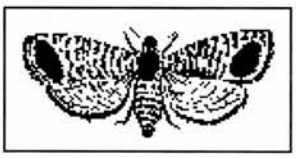

Figure 2-3 Codling moth adult (From Pedigo, 1996, p524)

The life cycle of the codling moth is illustrated within Figure 2-4. There are four main phases within the codling moth's life cycle of development: egg, larval, pupal and adult stages. (Lischke, 1992).

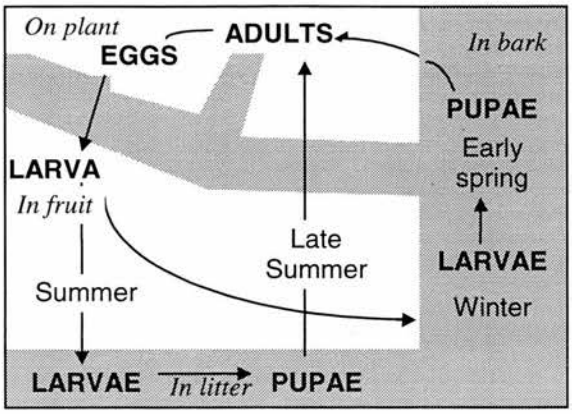

Figure 2-4. Life cycle of codling moth (*Cydia pomonella*)

Where pesticides are being used as part of control strategies, the ability to time the 'window' of application between 10% and 90% development of the larval stage is critical. Secondary problems may also arise since damage from direct tunnelling activity by the larvae provides a route for disease. While *Cydia pomonella* is in general considered to be rather sedentary, some individuals have been discovered having undertaken flights of several kilometres in the field (Schumacher *et al.* 1997).

A common approach to minimise the level of attack in commercial orchards has been the use of broad-spectrum insecticides applied using standard formulae. Pheromone traps, to which adult males are attracted, are used to sample insect population levels: if the catch exceeds the given pre-determined threshold (e.g. 5 adults/trap, per Gratwick 1992) then the recommendation is that the crop is sprayed one week later. The aim is to kill young larvae before they cause serious damage (Morgan 1991). More recently, mathematical models in conjunction with the trap catch data have been used to provide a more flexible estimate of the date at which the chemical treatment will have maximum effect (e.g.'PEST-MAN', Morgan and Soloman 1993). However, recent development of organophosphate resistance has limited the effectiveness of such programmes and additional bio-intensive management tools are needed to replace the broad-spectrum insecticides for control of codling moth. Within a European context, insect growth regulators such as fenoxycarb have been used to control *C. pomonella* in many fruit growing areas, making integrated programs possible (Riedl *et al.* 1995). The use of granulosis virus is a further 'bio-rational' tool used to reduce deep entry of larvae into apples, its short span of effectiveness again prompting the need for more accurate phenological predictions.

2.1.2 Modelling pest development: the role of temperature

The focus of this thesis is on the geographical element of modelling pest phenologies. It is therefore necessary to gain a basic understanding of the pest life cycles being modelled, critical data inputs and outputs and model structures not only to ensure that the models are correctly linked but also to assist in interpreting the results.

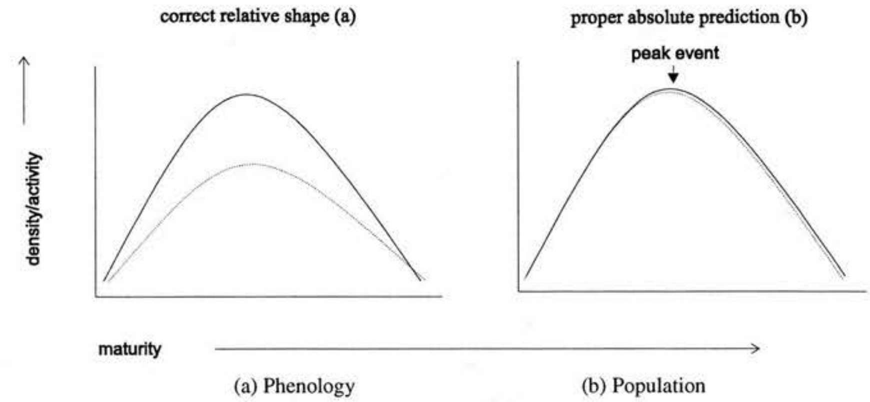

Figure 2-5. Pest maturity distributions in phenology vs. population models, after Welch *et al.* (1978)

Before launching into details regarding specific models, it is particularly important to stress that it is the timing of the pest life cycle, not population (actual numbers), that is the focus of this current research effort (Figure 2-5). Emphasis is being placed upon the geographical prediction of modelling the timing of developmental stages (*phenological* modelling), not the absolute numbers of pests expected (*population* modelling). A multiplicity of factors affect insect populations, such as prey/predator interaction, competition, the availability of a preferred habitat and food sources. These combine in a complex manner to make local scale dynamic modelling intensive on both data and computation, and impractical as a means from which to create national pest risk assessment except by assuming the most simple, non-limiting environment for pest development. Insect phenology is driven primarily by temperature, with the availability of suitable food an influential secondary modification (Baker 1980).

The use of ambient temperature/time relationships, to estimate an insect's progress through the life cycle, has long been established (e.g. Réaumur 1735, in Higley *et al.,* 1986). As poikilothermic (cold-blooded) organisms, insects develop at rates in proportion to ambient temperature: they cannot regulate their own body temperature. Insects do however seek thermally favourable habitats, and have developed genetically to become efficient 'black body' absorbers of solar radiation. As such this association between temperature and growth is not straightforward (Figure 2-6), and depends on the rates of a number of basic level biochemical reactions. Individual rates for these enzyme catalysed processes depend on three criteria: the availability of

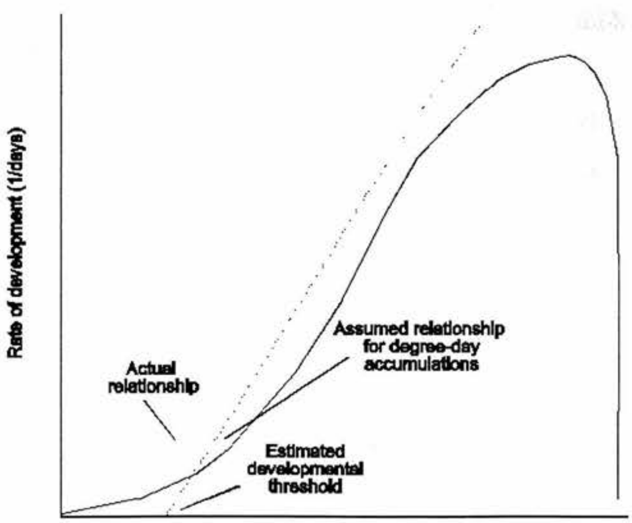

Figure 2-6. Relationship between rate of development (1/time) of insects with temperature (After Pedigo (1996), p196.

substrates, the availability of enzymes and temperature (Higley, Pedigo and Ostlie 1986). Enzymes, for example, need not be regulated by temperature alone but in some cases may be regulated hormonally, through factors such as genetics or photoperiod.

When investigating insect development rates, it is common experimental practice to rear insects of each stage of the lifecycle (e.g. egg, larvae, pupae and adult) in temperature regulated incubators at a range of different *constant* temperatures. The mean rate of development against temperature may then be plotted for each stage, from which data a number of methods may be employed to fit the underlying developmental curves. The manner in which the experimental development rate plots are interpreted has become more sophisticated over time. This section discusses three distinct approaches that currently appear within the applied entomological literature and that are used in practical applications today.

The first approach applied to the modelling of insect development rates is commonly termed the 'day-degree' method, and may also be found in connection with crop (e.g. Hallet and Jones 1993, Perry *et al.* 1997) and heating engineering (e.g. Hargy 1997) models. In this most simplistic of methods, the rate of development of an organism is assumed to be linear, and identical across all life stages. Hallett and Jones (1993) describe it as the '*integrated excess or deficiency of temperature about a fixed datum'*. Degree-day models are specified in terms of developmental threshold and thermal constant. The *developmental threshold* represents the minimum value below which no development takes place, while the *thermal constant* is the number of degree-days required for an event to occur. By associating thermal constants with particular events, such as hatching, each larval molt, pupation and adult emergence, a model of the insect lifecycle may be developed. As Baker (1980) points out, however, accumulated temperature models have the unfortunate effect of blunting important irregularities in maximum and minimum temperatures where minima fall below the base temperature. In a British context, with highly variable and rapidly changing weather conditions, the incorporation of such lower temperature limits is particularly important. Additionally, the simplicity of the model makes the accommodation of other factors such as photoperiod, which often plays a subsidiary role at oviposition or diapause, problematic. While Pitcairn *et al.* (1992) use this type of degree day model for predicting multiple generations of pests, the general consensus is that overlapping between generations makes such figures unreliable (e.g. Blago and de Baradinis 1991).

The second method discussed presents a more realistic assessment of pest development rates. Rates may vary between stages which, given the physical variation and changes in environmental situation of an organism between life stage, is an intuitive development from the earlier model type. The organism switches within the model to the next developmental phase once particular accumulated temperature thresholds are reached. Instead of using an approximate mean base temperature appropriate to the test insect, separate base temperatures are required for each stage in the life cycle. This has the implicit effect of altering the individual development rates per stage. The general form of each individual curve however remains linear. The multiple thermal constants required are most commonly established in laboratory studies, and errors in estimating base temperatures are the most common cause of error in model predictions (Collier *et al.* 1991). Despite the fact that such variations with life stage have been common knowledge since the 1960s (Wang 1960), however, the use of the simpler model structure has persisted, perhaps owing to its simplicity of approach and predictive adequacy.

As shown within Figure 2-6, the rate of development of an insect over time has been found to be broadly curvilinear, rather than linear (Sharpe and deMichele 1977, Liu *et al.* 1995, Worner 1992). The non-linear portions of the plot are a consequence of inactivation of the control enzyme, or enzymes, at low or high temperatures. Temperatures for example may be so high as to cause structural changes in the controlling enzymes, impair enzyme function or actually denature some proteins (Higley *et al.* 1986). For *C. pomonella*, for example, the rate of development increases up to 30-32°C and then rapidly decreases subject to stage (Rock and Shaffer 1983). The precise shape of this upper, and indeed lower, curve may vary considerably with the variance of the underlying temperature which has led some modellers to remain with accumulated temperature methods but to specify a 'biofix', or starting date for accumulation that is biologically distinctive. A number of researchers have acted on the biophysical findings of researchers such as Sharpe and deMichele (1977) and introduced curvilinear development rates within more complex models (e.g. Phelps 1993, Stinner *et al.* 1974, Logan *et al.* 1976) with varying success. In contrast with the earlier model structures, progress through the life cycle is calculated explicitly by development rate, rather than threshold. Malet *et al.* (1997) suggest that such use of development rates is preferable to the use of cumulated indices for bio-environmental relationships in general, arguing that these often exhibit high correlations between them and the likelihood of introducing statistical artefact is high and therefore should be avoided. Linear models in several studies have however been found to perform equally as well as more complex non-linear models, and are easier to implement in a forecasting system (Hochberg *et al.* 1986, Worner 1992). This is particularly the case where data at either temperature extreme are sparse, making non-linear curves difficult to fit reliably at their extremes.

Discussion within the literature regarding the means by which temperature and development are related indicates that developments in computing have allowed a movement away from simple accumulated temperature models to those employing multiple thresholds and combinations of parameters. Whatever the structure of a phenology model, evaluation of its predictive capacity using field data remains vital (Worner 1992, Pruess 1983) for applied work. Since laboratory temperatures do not reflect the varied environment in which pests live and temperatures in field conditions are not constant, estimates of development rates in the field are likely to differ from those obtained under laboratory conditions. Development under a fluctuating regime, outside the regulated laboratory environment, may well be different from that arising under constant temperatures, for example (Worner 1992). Campbell *et al.* (1974) suggest that the magnitude of this discrepancy depends on the average temperature, amplitude and frequency of the fluctuations. Similar considerations are important when modelling mortality as well as development, an area of current entomological research. The validation and re-calibration process also may introduce error, since trap catches used to determine the extremes of the development process may themselves vary according to the underlying population volumes. To be of practical use any risk assessment system must be capable of using standard meteorological data (Phelps *et al.* 1996).

2.1.3 Insect phenology models within a broader environmental modelling context

In environmental modelling and GIS terms, the three categories of applied entomological process models discussed may be summarised as dynamic 'lumped' models; that is, while the inputs and parameters may change with time, their estimates are space invariant. Mathematical in nature, the majority of examples remain deterministic (e.g. Morgan 1992) although stochastic phenology models are becoming more widely adopted (e.g. Finch *et al.* 1993). Model typologies vary from author to author depending on their focus on model derivation and process orientation (e.g. Heuvelink 1998), stochasticity and temporality (e.g. Steyaert 1993) and spatial extent (e.g. Burrough *et al.* 1996). Others use similar, but implicit, constructs (e.g. Maidment 1993).

Table 2-1. Model classification (After Burrough, 1991)

Category	Biological examples
Simple conceptual	e.g. 'one stage' temperature budget models
Conceptual process	e.g. Non-linear development rate curves, varying development rates by stage, threshold temperatures for ecdysis
Complex physical	e.g. explicit consideration of enzymes/chemical reactions underpinning development

Of alternative schema, one of several used by Burrough (e.g. 1996, 1991) and which is based rather upon model complexity, fits the biological perspective discussed most closely (Table 2-1). In particular, it avoids distinguishing between the often-inseparable use of both empirical and conceptual approaches within one model (e.g. Johnston *et al.* 1996). The empirically based temperature budget model used in this study can for example be classified as a 'simple conceptual' approach. The strong dependence of insect development rates on temperature forms the underlying concept, but the translation into model form is strongly empirical and may ignore important biological realities such as insects developing at different rates during the various life stages. The more advanced models incorporated within this work might be categorised as conceptual process models despite containing simple rule-based thresholds as important components of ecdysis functions (e.g. Baker and Cohen, 1985). The enforcement of linear rates of development is a simplification avoided by such models, which may for example use a logistic function to model development and so mimic variable chemical reaction rates (e.g. Morgan 1992). More unusual within applied entomological work are complex physical models explicitly accounting for chemical reactions or the breakdown of enzymes based upon the work of Sharpe and deMichele (1977) owing to their high data requirements although exceptions may be found (e.g. Lerin and Koubaiti, 1998). The similarity of form between the resultant rate curves and those of the conceptual process models serves to strengthen confidence in the latter.

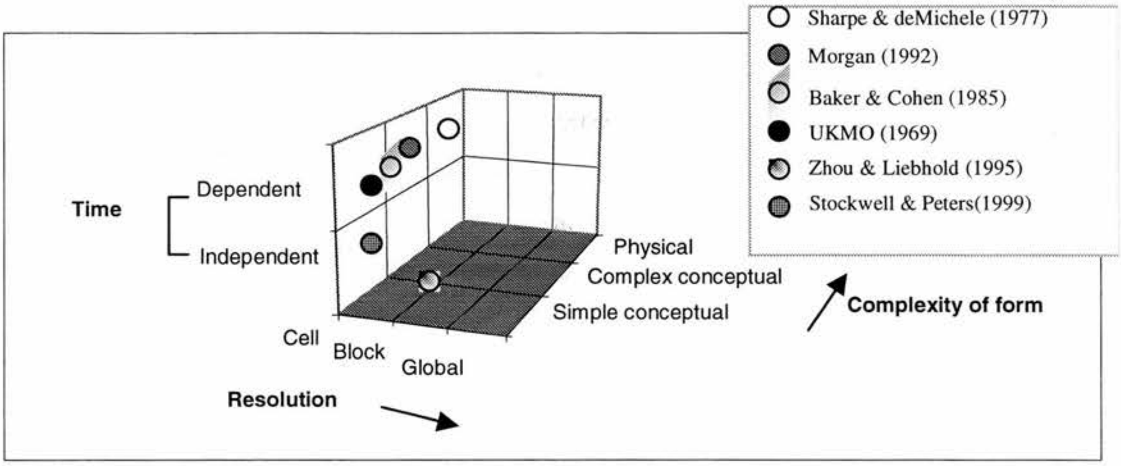

Figure 2-7. Classification of example biological models referred to within the discussion

Exploring the models according to their coupling with spatial data however, the schema of Table 2-1 requires expansion. Figure 2-7 illustrates the position of the biological models used within this study within a time/space/form classification space. In temporal terms, present models in insect ecology are complex in relation to time-independent automata type rule based models (e.g. Coughlan and Running 1996, Stockwell and Peters 1999). In comparison to other empirically defined models mimicking local, spatial interactions however (e.g. Zhou and Liebhold 1995), the approach is weak. 'Between field' rather than within field spatial modelling is the exception in applied insect ecology (e.g. Halley *at al.* 1996) rather than the rule (e.g. Morgan 1996) owing to the complexity of biological experiments needed to parameterise the models (e.g. Thomas and Jepson 1997). Within the broader theoretical population modelling literature, as in the broader environmental modelling and GIS arena, this distinction is less clear: Lotka-Volterra type models for example take spatial clustering into account in modelling predator/prey relationships and 'space' has been a major research thrust in insect ecology over the past decade (e.g. Amarasekare 1998, Durrett and Levin 1998, Garrett and Dixon 1997). Gaps in the basic understanding of spatial insect ecologies in relation to actual environmental influences down at the field scale (1-100m) limit this study, which focuses rather on landscape wide relative space-time fluctuations between years in insect phenologies. In methodological terms, the current framework for risk assessment is much simplified in the spatial dimension in comparison with the platforms afforded by Westervelt and Hopkins (1999) or Van Deursen (1995). For future modelling opportunities however, the ability to design and construct pest and crop models within a single structure with common inputs as other spatially distributed models that run on a daily basis remains an important goal.

Limiting Figure 2-7 to three axes ignores the important stochastic/deterministic modelling element incorporated by Steyaert (1993). It is a reflection on current process with error propagation methodologies that models incorporating stochasticity, both within insect ecology and more generally within environmental modelling and GIS, tend to be of the simplest type. The use of logical models for example, such as the rule based insect population studies of Downing and Bartos (1991) and Loh *et al.* (1991), facilitates the incorporation of certainty factors within analyses. Similarly, automata models have been derived on the basis of empirical data to provide probabilities attached to modelled distributions on the basis of Markov chains (e.g. Zhou and Liebhold 1995). These findings are also echoed beyond insect ecology (e.g. Johnston *et al.* 1996, Stockwell and Peters 1999, Coughlan and Running 1996, Stassopoulou *et al.* 1998).

2.2 Insect ecology: geographical perspectives

While ecologists might choose to disagree with Kareiva's (1990) opinion that space is the 'final' frontier in their discipline, it is certainly the case that over the past five years there has been a growing interest among biologists in setting their work within a spatial context. Realisation that location provides a common reference for the integration of more than one process has fostered interest in a more complete system approach. Within the sub-discipline of insect ecology the trend is similar, although most work remains 'spatial' as opposed to 'geographical': it lacks reference to real-world location, and has focused on relationships and movement within a locally homogeneous or at best unrealistic environment (e.g. Zhou and Liebhold 1995). Work incorporating well-established relationships between climate and insect development, between crop/pest and predator/prey in a realistic geographical framework has been slow to materialise owing to the need for more fundamental biological understanding between individual elements and their inter-relationships. In Fedra's (1993) terms, there is a continued focus within insect ecology on 'state' rather than 'location'. Rarely are both issues addressed *together* in this setting, although attempts to date suggest that the combination can open up new opportunities since the incorporation of location provides a common reference for the interaction of more than a single biological process. Geostatistics (stochastic spatial statistics) and geographical information systems (computing frameworks for the management and analysis of spatial data) have for example been enrolled at some level to:

- Assess the potential for establishment of non-indigenous pests (e.g. Baker 1994);
- Assess the likelihood of entry into a country of non-indigenous pests (e.g. Sutherst *et al.*1991);
- Suggest environmental factors critical to indigenous pest development (e.g. Sheperd *et al.* 1988, Johnson 1989, Evans *et al.* 1996);
- Improve understanding of dispersion rates by a geographical analysis of distributed trap data (e.g. Liebhold *et al.* 1992);
- Evaluate the probable effect of climate change on the range of a variety of species (e.g. Jeffree and Jeffree 1996, Williams and Liebhold 1995, Baker *et al.* 1996, 1998);
- Provide pest risk forecasts using observed sequences of historical data from distributed traps (Gage *et al.* 1990), environmental rule bases (Downing and Bartos 1991, Loh *et al.* 1991) or from linked phenology models (e.g. Russo *et al.* 1993, Régnière and Bolstad 1994, Schaub *et al.* 1995*a*);

- Improve spatial sampling for pest monitoring within management programs (e.g. Weisz *et al.* 1995, Liebhold *et al.* 1991, Schaub *et al.* 1995*b*) and control practices that are targeted in space on the basis of a sample network (Weisz *et al.* 1996).

The focus for discussion in this section, given the context of the study, rests on the landscape wide modelling efforts made to date. Organisation of the review, in keeping with the twin applications of the geographical phenologies constructed for the study, is made according to the indigenous/non-indigenous status of the pests modelled.

2.2.1 Geographical slants upon pest risk assessment: non-indigenous pests

Both the WTO (World Trade Organisation) Sanitary and Phytosanitory Agreement and the IPPC commit members to justify quarantine assessments scientifically, transparently and without discrimination (Hedley 1994, Hopper 1991, van Halteren 1996). The need for new methods to support PRA is becoming particularly important since, as Waage (1996) notes, '*We are already seeing the new invasion routes of the future – North-South and South-South trade in horticultural produce, bringing whiteflies, leaf miners, thrips and mealybugs around the world, the opening of trade with the former Soviet Union and China, bringing crop and forest pests like Asian gypsy moth to other temperature regions and other new pests back into Asia*'. Many of the typical questions addressed within this broad process of combining, interpreting and communicating that is pest risk assessment are inherently geographical, as the subset of potential questions that need to be answered as part of a pest risk assessment illustrated within Table 2-2 identifies. The particular issues addressed within this study, owing to its phenological focus, are those which contribute to determining the long-term probability of establishment of particular pests, itself a sub-component of the assessment phase. Others have for example employed geographical techniques to investigate the probability of a pest's initial importation (e.g. Cohen 1998, Sutherst *et al.* 1991) or understand the spread of an establishing species (e.g. Nash *et al.* 1995, Schaub *et al.* 1995(a), Sharov *et al.* 1998).

Table 2-2. Typical data required for assessing the risk posed by a non-indigenous pest (After Kehlenbeck, 1996)

Host plants	Data concerning the pest	The endangered area
• which host plants may be damaged? • area and/or number of host plants; • monetary value (production value, value according to the concept of willingness to pay); • importance for the area (considering terms other than monetary).	• damage (kind of damage, amount or % reduction); • biology (number of generations, demands on abiotic conditions); • spread rate (how long will it take for the whole area to be infected?; • protection and eradication measures (availability, effectiveness, costs, side effects).	• where are the abiotic factors which favour the pest? • which is the endangered area? • host plants within this area?

The continued popularity of the climate matching CLIMEX program (Skarratt *et al.* 1995) for the risk assessment of insect pests for pest risk assessment, while not technically a GIS, exemplifies the continued influence of inductive work based upon climatic variables in insect ecology. For these reasons, in addition to its widespread use in pest risk assessment and mapping facility, the relative merits and assumptions within CLIMEX deserve further discussion under this heading. The CLIMEX system reported here should not be confused with the climate change programme of the same name (e.g. Beerling and Woodward, 1994).

CLIMEX may be summarised as a modernisation of the bio-climatic studies of researchers such as Cook (1925). Using the most comprehensive database of pest observations possible, these data are used to calibrate the model by association with the climate normals at the nearest known points to the data. In a user-driven, iterative process, climate parameters such as seasonal rainfall or maximum temperature are altered until the estimated pest distribution (presence/absence/levels of damage) matches that of the known data. However, this CLIMEX approach carries a number of intellectual disadvantages, many of which relate particularly to the inductive methodology. It is where data are limited that the approach is more likely to be inaccurate: positive inference will be reliable but potentially incomplete. Apparent stress factors may in fact relate to the population front of a dispersing but not fully established species, poor sampling plans or chance observations in remote areas. Additionally, the array of climatic parameters the system uses to match locations are many, from soil temperature and moisture to temperature and precipitation, yet few may have a direct bearing on any one insect and invocation of the user's biological expertise is critical in this respect. Broader consideration of influences other than climate is not however facilitated. Together, these shortcomings, documented elsewhere in more detail (Sutherst *et al.* 1995), pose considerable drawbacks to the use of CLIMEX for PRA. Pragmatically, CLIMEX provides a useful tool for assessing the likelihood of establishment of non-indigenous pests in the absence of detailed process models for an organism. Its national and international perspective is unusual within insect ecology, where the more common scale of study is within the individual field. It should however only be used in the hands of an experienced biologist.

Assessments within CLIMEX may alternatively be made on the basis of externally derived biological parameters such as accumulated temperature thresholds that are then compared with those of the potential destination country. Implicitly therefore, the CLIMEX software draws as much on concepts of pest phenology rather than population for PRA, as is the case in this study. Phenology models however less commonly incorporate modules to account for stress or mortality over winter, and CLIMEX's consideration of winter temperatures in addition to conditions for development over the summer is one of its main reasons for continued popularity. The manner in which it accounts for overwintering processes is however highly empirical, especially given the monthly climate normal data used to construct the stress indices when compared with the known complexities of overwintering processes according to fluctuations in daily temperature (Leather *et al.* 1993). However, unlike process-based phenology models which are more sensitive vehicles for reporting the predicted timing of particular stages in insect development, in this case the results are scaled into population growth index and stress indices, and combined in an overall *Ecoclimatic Index* on a scale of 0 – 100 where high values indicate strong probabilities of survival. This represents the potential ability of a pest to thrive at any one location, computable where sufficient climate data are available for comparison with the specified environmental conditions. The ecoclimatic index thus has a specific meaning for each particular organism modelled.

In either form, inductive or deductive, results from CLIMEX are presented as point data confined to the location of known meteorological recording sites and are based on monthly aggregated climate indicators rather than the daily records more commonly used when modelling indigenous pests. However, as a number of researchers have demonstrated (e.g. Baker *et al.* 1996, Yonow and Sutherst 1998), it is also possible to adapt CLIMEX to use interpolated spatial climate data such as the 1961-90 monthly climate normals available from the Climate Research Unit (Hulme *et al.* 1995) to provide fully spatial pest risk indices. Such outputs present a fuller picture of establishment potential, although the quantitative impact of this approach on the assessment of long term establishment possibilities appears not to have been explored.

The limitations of CLIMEX for pest risk assessment are most commonly acknowledged in terms of its inductive base, as above. Less commonly discussed is the effect of using monthly long-term climate averages, which will hide potentially significant inter-year fluctuations. Critical periods of pest development may occur within the context of one month. Important development thresholds may therefore be masked using monthly data, and most models of indigenous pest development run using daily inputs in reflection of this fact. Additionally, depending on where these point locations are, the modelling results may not be representative of the overall target landscape or relevant to cropping areas. This issue was raised by Royer *et al.* (1989) in the context of assessing risk from non-indigenous diseases, and echoed by Baker (1994) in a precursor to this study, but quantitative comparisons between point, regional average and fully spatial assessments have not yet been explored. Moreover the ecoclimatic index is of limited value in assisting with control strategies in the event of an outbreak owing to its 'relative' nature: it does not provide any indication of the timing of insect development. Useful management information would be more easily extracted from the results of a deterministic phenological process model, which would specifically provide estimated insect emergence dates for different developmental stages, where available. Few if any examples exist of such phenology model results being used in a fully spatial manner for non-indigenous pest risk assessment at national level. As Walker and Young (1997) reflected in a GIS context, '*Quantitative aggregation to provide the statewide and national perspective sought by those who shape policy directions is unusual*'

Drawing upon literature from areas where the pest is established, Baufeld *et al.* (1996) also perform eco-climatic comparisons in their assessment of the establishment of *Diabrotica virgifera* on maize in Germany but outside a CLIMEX environment. Using their expert understanding that the pest does not have exceptional requirements for moisture but rather that development is largely temperature driven, monthly and seasonal normal temperature maps are used to draw conclusions regarding establishment.

However, distributions in relation to locations where maize is actually grown or overall areal statistics are not estimated. Again in a German context, accumulated soil temperature normals are used to assess potential damage from the polyphagous nematode *Meloidogyne chitwoodi* (Braasch *et al.* 1996). Seasonal and annual figures and risk are summarised by region, but the means by which these are computed and aggregated is unclear: the use of data from a few selected meteorological stations is assumed. The use of long-term means in both these studies, like CLIMEX, obscures the annual variation in risk posed. Additionally, the statistics are not summarised in relation to potato growing areas although digital cropping data appears to have been mapped; an example of GIS used to display, but not exploited to its full analytical potential.

From a technical phenology modelling perspective, accumulated temperature measures are a valuable tool for assessing both the risks posed by non-indigenous pests (e.g. Tiilikkala *et al.* 1995, Braasch *et al.* 1996) and indigenous pest management (e.g. University of California Statewide Integrated Pest Management Project Phenology Model Database, http://www.ipm.ucdavis.edu). While relating to plant disease, the assessment of risks posed by fireblight to Australia from trade with nearby New Zealand (Roberts 1991) also reflects a preference by some scientists to use deductively derived process-based models in both settings. In addition to identifying different aggregated climatic patterns according to production area, Roberts' study is unusual in reflecting the importance of season-to-season variability. Such results, unlike the main body of work in pest risk assessment, provide insights into the underlying variability and consequent sensitivity of the biological model to differences in climate data at different geographical locations. Also bridging the gap between geographical work on non-indigenous and indigenous pests are those studies concerning the early spread of a pest within a country or region (Nash *et al.* 1995, Schaub *et al.* 1995a, Sharov *et al.* 1997). Additionally, a number of the pests modelled as indigenous organisms by one group of researchers (e.g. gypsy moth, spruce budworm) and therefore discussed in the next section are regarded as quarantine pests in a British context. Indeed, the codling moth modelled within this project as a representative indigenous species to England and Wales has until recently been the subject of quarantine checks in Japan. This overlap suggests the possibility that existing phenology models or accumulated temperature information may be available for pests common to overseas trading partners.

2.2.2 Landscape wide approaches to the modelling of indigenous pests

Just as CLIMEX is often used inductively to estimate the potential distribution of little known non-indigenous pests, outbreaks of native pests have also been related to particular biological and physiological features of the landscape (e.g. Sheperd 1988). A previous review by Liebhold *et al.* (1993) shows a particular bias towards such inductive modelling in the earlier work using GIS for insect ecological purposes. There are also a number of similarities in the approaches used for both non-indigenous and native species when PRA uses phenology models to generate risk at a particular location. In particular where phenological models are used to enhance control practices, either biological or chemical, decisions are still most commonly made on the basis of point predictions. In a

British context, traditional paper outputs have been converted to interactive GIS based 'semi-spatial' risk assessments. These are based upon deductive process models run at a necessarily limited number of sites where sufficient meteorological readings have been made (e.g. Parker and Turner, 1996). However, in producing these 'dot maps' of risk at points, the underlying assessment procedures remain tied to a single localised point and as such are fundamentally unaltered. As Goodchild (1993, p12) reflected, '...*many applications of GIS technology turn out to be little more than digital cartography*'. Thus, whilst the current generation of British agricultural decision support systems incorporate models whose development is 'state of the art' in biological terms, their development from the viewpoint of environmental/meteorological input data is less advanced.

Within a wider European setting, government led initiatives have led to relatively dense agro-meteorological recording networks (e.g. Hoppman and Holst 1996, Rantanen *et al.* 1993, Denzer 1996). From these point data regionally averaged estimates of risk have been estimated and subsequently been mapped using GIS. Pl@ntInfo (Jensen *et al.*, 1997) provides an example where local predictions of both pests and diseases appear to have been aggregated to provide summary information, distributed over the Internet. No isolation of the error that arises specifically as a result of basing decisions on model results that may be unrepresentative of particular farm location (as opposed to error within the biological model/these sources of error combined) has been found within the ecological research literature. The GIScience literature points to errors that may arise when localised data are aggregated over much larger areas. For this reason, caution is needed and uncertainty should be estimated when producing aggregate summaries.

Table 2-3. Previous research into the prediction of landscape wide pest risk for indigenous species as a component of IPM on the basis of phenology

INTEGRATED PEST MANAGEMENT **(Phenology based)**	Pest/disease	Geographical Area	Method	Guiding variables
Régnière (1996) Régnière and Bolstad (1994)	Spruce Budworm (*Choristoneura fumiferana*)	New Brunswick	Trend surface interpolation of target events (Julian dates, % emergence)	Elevation, exposure, pre-partitioned climate zones to account for maritime influences
Schaub *et al.* (1995a)	Gypsy Moth (*Lymantria dispar*)	Virginia, West Virginia, Pennsylvania and Utah	Linear regression of Julian date with height	Elevation
Russo *et al.* (1993)	Gypsy Moth (*Lymantria dispar*)	West Virginia, Pennsylvania	Trend surface interpolation of daily temperatures	Elevation

Table 2-3 summarises the present state of published research in geographical science for the 'fully spatial' mapping of indigenous pest phenologies. Most of this work is found within a North American context. This group of literature follows the most similar approach to the strategies proposed in this thesis for both the indigenous and non-indigenous pest modelling. In particular, taken together the papers by Russo *et al.* (1993), Régnière and Bolstad (1994) and Schaub *et al.* (1995b) reflect the current understanding on the value and the derivation of spatial phenologies.

Past work modelling spatial phenologies has taken two main approaches, differing markedly in both their modelling and computational complexity. An example of the first approach is the work of Russo *et al.* (1993). This draws on the known relationship between pest development and temperature, on which basis individual trend surfaces of daily temperatures using latitude, longitude and elevation are modelled. These are then used to drive an originally at-a-point model to provide estimates of risk at each $1km^2$ interval throughout a raster grid. In contrast Schaub *et al.* (1995a,b) and Régnière and Bolstad (1994) both take the simpler approach of running the phenological model to produce point based results and then using an interpolation method to convert these into continuous gridded estimates of risk over the whole landscape. Aside from the obvious issues of computational complexity, little consideration is given to the rationale behind the two strategies. This is an important oversight because research in GIScience is presently focusing attention on how the choice of interpolator and the sequence of interpolation/modelling operations can lead to significant differences in outputs over geographical areas (e.g. Burrough 1992). Assessing the differences between these two approaches in terms of their relative accuracy and spatial coherence forms an important strand of experimentation within this work (Chapter 6). Risk maps that do not provide outputs that follow the correct biological development sequence at particular locations over time for example will afford little biological credibility in the eyes of their potential users. Equally, from a GIScience perspective, the sweeping assumptions regarding the stability of spatial autocorrelation over both space and time that are current practice provides little theoretical comfort.

As Table 2-3 indicates, most of these studies use elevation to assist in the interpolation of both temperatures and pest phenologies. The interpolation methods that have been used are relatively simplistic: both lapse rate modelling and trend surface analysis have long been used in environmental studies but more sophisticated techniques (e.g. partial thin plate splines, kriging) are less commonly incorporated in applied studies. Schaub *et al.* (1995b) for example use a linear regression function of Julian date with altitude that is based upon data from one site only, and employ an unvarying annual lapse rate to produce a notional relationship between phenology and elevation. While meteorological site data can often be sparse, this use of one station only would seem likely to introduce a strong bias into the results. Additionally, within the meteorological literature, such use of temporally averaged lapse rates is no longer considered appropriate, even when modelling monthly temperatures (Cramer and Fischer, 1996). Perhaps unsurprisingly, Schaub *et al.* found their lapse rate models for both egg hatch and larval emergence to be region specific, indicating that greater focus upon improving the predictions of underlying temperature down at daily and sub-regional levels would be useful. This subject will be addressed within chapter 4. The need to distinguish between input and biological error is supported by comparison of Schaub's results with those of Russo *et al.* (1993). Although the phenology models used in the two studies were identical, the starting date from which larval development was simulated differed and large discrepancies were found. Partitioning error between improvements in the biological, as opposed to the geographical, modelling approach is thus fraught with difficulty. This is a topic that will be explored in chapter 7.

The work of Régnière (1996) represents the most sophisticated approach to the construction of geographical phenologies to date. Similarly to Schaub *et al.* (1995b) insect model results are interpolated using a trend surface in latitude, longitude, elevation and an 'exposure index' to predict insect development across the landscape at scales between 30-100m over an area of study approximately 100km^2. However, there is little focus on either the effects of the volume of *sample* data, *placing*, or *interpolation* technique within Régnière's work. Interestingly, he makes the apparently intuitive suggestion that interpolated temperatures, rather than phenologies, be used where data are sparser. However temperatures are not in fact interpolated and there is no formal analysis of the relative merits of the two approaches, or of spatial autocorrelation and data configuration. The work proceeds rather with the uncritical assumption that, whether mapping population numbers or dates of emergence, these can be interpolated successfully. From a GIScience perspective, there is a need to use a method of interpolation that is most appropriate to the spatial structure and nature of the point-based phenomenon under scrutiny.

Clear precursors to this study may also be found within the application of spatial phenologies in the crop disease literature (Royer and Yang 1991, Seem 1993, Seem *et al.* 1991). The link between potential use of spatial phenologies for both indigenous and non-indigenous pest assessments may be seen in the suggestions and early experiments of Royer and Yang (1991) investigating the risks posed by soybean rust. In contrast with work on pests to date, greater attention has been paid within the disease literature to the underlying climate modelling used to drive phenologies. Ambitiously for his time for example, Royer *et al.* (1989) downscaled numerical weather model outputs to generate daily phenological model inputs such as temperature, rather than relying on empirical interpolation techniques. The use of downscaled numerical model data versus interpolated data is explored in greater detail within the methodology (Section 3.2.1, p80). Broadly, numerical methods are considerably more computationally intensive than interpolation and are rarely downscaled to the 1km^2 resolution required for risk assessments at a national rather than regional level owing to the detailed land cover information required. Seem (1993), in a rather over-enthusiastic overview of GIS for localised pest predictions using meteorological variables, suggested that when 1km^2 data are available it should be possible to compute the timing of the development stages for insects, infection periods of pathogens and even pest densities. The paper highlights difficulties with the costs and availability of input data such as of elevation and or soil type, even in an American context and suggests possibilities for work rather than reporting results. In a more detailed study, Seem *et al.* (1991) interpolated temperatures to a resolution of 100m^2 over a 320km^2 area of southern Norway in the context of pathogen risk assessment but found their results disappointing, most likely due to a paucity of initial temperature recordings. While the context of their work was to provide data for risk assessment, no biological models were coupled with the interpolation system as in this study.

Table 2-4. Previous research regarding the prediction of risk to crops on the basis of indigenous pest population estimates and consequent predictions of defoliation using geographical concepts

INTEGRATED PEST MANAGEMENT **(Population based)**	**Pest/disease**	**Geographical Area**	**Method**	**Guiding variables**
Downing and Bartos (1991)	Mountain Pine Beetle (*Dendroctonus ponderosae*) Probability of outbreak	South Eastern Wyoming, Medicine Bow National Forest	Expert system	Critical temperatures Elevation, stand diameter
Gage *et al.* (1990)	Gypsy Moth (*Lymantria dispar*) Adult catch and % defoliation	Michigan State, USA (1km^2 grid)	Distance weighting and temporal regression	Latitude, longitude and elevation
Gribko *et al.* (1995)	Gypsy moth Defoliation record and egg mass counts	Massachusetts State (2km^2 grid)	Kriging and logistic regression	None
Hohn *et al.* (1993a)	Gypsy moth Defoliation	Massachusetts	Indicator kriging	None
Hohn *et al.* (1993b)	Gypsy moth Defoliation	Massachusetts	3-D indicator kriging	None
Liebhold *et al.* (1995)	Gypsy moth Defoliation record and egg mass counts	Appalachian parks (1ha^2)	Kriging and logistic regression	None
Liebhold *et al.* (1998)	Gypsy moth Defoliation record and egg mass counts	Appalachian parks (1ha^2)	Kriging and logistic regression	None
Loh et al. (1991)	Jack Pine Budworm (*Choristoneura pinus*) Risk rating for defoliation	Hiawatha National Forest (Highly Localised)	Expert system	Soils, forestry, stand size, stand age (multiple local factors)
Weseloh (1996)	Gypsy moth Defoliation record and egg mass counts	Connecticut	Ordinary kriging and logistic regression	None for kriging, elevation, soil, location in logistic regression
Zhou and Liebhold (1995)	Gypsy moth	Massachusetts (2km^2)	Cellular automata	None

The second body of work modelling landscape wide pest risk, detailed within Table 2-4, identifies risk in terms of populations rather than phenologies. Liebhold's group is particularly dominant among those (e.g. Loh *et al.* 1991, Downing and Bartos 1991) modelling defoliation percentages on the basis of historical records of damage and current population samples. Overwhelmingly, this work is highly empirical. For example, both egg mass densities (e.g. Liebhold *et al.* 1998) and adult catch (Gribko *et al.* 1995) have been kriged, and relationships between the mapped outputs and records of defoliation measured from aerial photography derived using techniques such as logistic regression and 3d kriging (e.g. Hohn *et al.* 1993a, Liebhold *et al.* 1996). In order to attempt such studies however, the volume of underlying sample data must be high: in the case of the Gypsy moth studies, pheromone trap data on a regular 2km^2 grid over a 5.5 million ha area in the Appalachians were used in addition to more locally intensive egg mass counts. The range of spatial autocorrelation between egg mass counts, for example, was found to be only 500m in this area (Sharov *et al.* 1996). This reflects the high dependence of population counts on a large variety of localised and interacting environmental and biological processes and signals the need for careful consideration of spatial autocorrelation before interpolating population counts in particular. Again in a forestry environment, European work is underway looking at the dispersal of *Dendroctonus micans* in the Massif Central at multiple scales (Gilbert 1998).

Similar empirical data which forms the basis for the work of Downing and Bartos (1991) is unusual in that it merges both phenological and population knowledge within an expert system framework. Loh *et al.* (1991), also using an expert system, demonstrate the use of certainty factors to propagate uncertainty within the modelling process. The scale of such expert system applications to date however has been highly local, and the use of forest stand and species records incorporated in such risk assessments is not currently practical for wider landscape models (e.g. Liebhold *et al.* 1998) where a lack of consistent digital land use mapping and the volume of data to be handled hinders such work. The intensive sampling systems required for these studies is an indication of the potential cost to the forestry industry should pest invasions be uncontrolled. Leibhold (1993) cautions, even within the context of a data-rich environment, that process-based pest population modelling rather than empirical interpolation or regression approaches is yet insufficiently parameterised for practical applications. In a British context and even when considering indigenous pests, such volumes of sample data on which to develop empirical assessment techniques (such as regressions of insect populations with location) are currently known to be insufficient. This inadequacy in actual pest sample data volumes also applies in the case of national model validation in the field: other means of assessing spatial (un)certainties need to be researched. These findings confirm the focus on phenologies within this study.

2.3 Issues at the interface between environmental modelling and GIS

Linking environmental process models with geographical information systems in order to model in both space and time domains has attracted considerable attention over the past ten years. Historically, however, the role of GIS has been through the use of the 2D data structures it provides to structure both raw and finished products of environmental modelling (Goodchild 1993, p14) while in contrast environmental models concentrated on representing process rates over periods of time. The entomological process models used in this study are a particularly extreme example of this type: rarely are they interfaced with GIS software, or developed with reference to geography. Progress in work modelling environmental process with/within GIS is exemplified within the 'Environmental Modelling and GIS' conference series sponsored by the American National Centre for Geographical Information and Analysis (NCGIA). The critical issue addressed in the many papers from a wide range of disciplines is the way in which the lack of temporal data structures within proprietary GIS may be overcome in order to support the extension of modelling work within a space-time context. Typical examples come from hydrology (e.g. Moore 1996) and ecology (e.g. Johnson 1993, 1996), and many have practical ramifications for improved management techniques or policy making. Recurring scientific issues underlying the many applied subject areas include integration issues (closely associated with treatment of temporality and also interoperability), data issues (including interpolation) and error propagation and visualisation/visual modelling environments. The focus within this review, given the broader context of the study, is placed on interpolation issues, potential sources of error and error propagation. Issues surrounding the coupling of process models with GIS are more briefly discussed.

2.3.1 Integrating process models with GIS

Early discussions regarding the integration of process models with GIS focused on the transmission of data between module units: the 'coupling' process. Options (loose, tight and embedded coupling) are now well rehearsed both in theory and practice (e.g. Fedra 1993, 1996, Nyerges 1993, Livingstone and Raper 1994, Karimi 1997). In his review discussing the links between environmental models and GIS, Nyerges (1993) explains these terms as follows:

> *'Coupling environments can range from loose to tight coupling depending on the compatibility of the data constructs and the software operations used to process them. A loose coupling involves a data transfer from one system to another. A tight coupling is one with integrated data management services.'*

While applications included within the first Environmental Modelling and GIS conference proceedings (Goodchild *et al.* 1993b) largely comprised models 'loosely coupled' with GIS, the structure of the second volume was equally split between models linked with GIS, and models developed within GIS. The simplicity of GIS modelling facilities of that time however (e.g. Berry, 1993) meant that, for the more complex integrative studies, loose coupling remained the only realistic option. Reflecting on the 'state of GIS', Goodchild (1993, p13) suggested that models which attempt to provide links to policy development are much more likely to rely on GIS for pre-processing of data given the wide range of considerations to be integrated within the decision making process. Prompted by this situation, research on integration issues has continued within two distinct strands over the past few years. The first focuses on improving integration through developing more appropriate data models and structures. The second has been the enhancement of the capabilities for modelling within GIS itself.

The separation of data structures from modelling functionality has been seen as crucial to progress within integration strategies (Abel *et al.* 1992, 1998, Kemp 1993). The development of spatial data structures that sit more easily with geographical concepts have been advanced using object oriented approaches (e.g. Livingstone and Raper 1994, Kemp 1997a,b). Agent-based strategies for example are among those that have allowed geographical entities rather than artificially imposed raster or vector structures to be used in modelling (e.g. Westervelt and Hopkins 1999). Questions arise however as to what the nature of spatial primitives for interoperable systems should be. Recognising that there is no 'best' data structure for all situations, Livingstone and Raper (1994) introduce the term 'semantic data model': a sub-discipline dependent higher level concept that unifies different underlying representations such that the entities define the space they occupy rather than being defined by it. Similarly, Rizzoli *et al.*'s (1998) 'domain base' for example focuses on problem definition rather than solution, building on Abel *et al.*'s (1992) earlier and less explicitly object-oriented work separating collections subsystem from operations subsystem. However, given the link between object and operator in object oriented design (Booch, 1991) discussion leads inevitably on to consideration of related operators and to modelling functionality intertwined with considerations of data structure.

Given the weakness of GIS in treating temporal data, developments in temporal data structures have formed a second, implicit, strand of the integration debate (e.g. Langran 1992, Peuquet 1999). Object orientation also forms a major strand in these temporal models (e.g. Ramachandran *et al.* 1994, Worboys 1999). It remains the case however that much of this work remains at a conceptual level (e.g. Wachowicz and Healey 1994, Ramachandaran *et al.* 1994): the development of ideas to the point at which they may readily be incorporated within applied studies or proprietary GIS frameworks has in general yet to occur. For the many applications where dynamic modelling requires spatial data inputs, including fire management, hydrological, crop yield, pest risk and nutrient transfer models (e.g. Kessell, 1996; Landau and Barnett 1996) therefore, barriers to fully integrated modelling within the GIS environment remain. As Peuquet (1999) acknowledges, the handling of temporal data remains a major research area in GIS. With moves towards greater use of object oriented code within proprietary GIS (Maguire 1999), a resurgence of interest in spatio-temporal data structures that may be implemented in standard rather than specialist systems might be expected.

Focus on data structure and database design has led naturally into one component of the wider debate regarding inter-operability between GIS (e.g. Sondheim, Gardels and Buehler 1999, OGC 1996), which attempts to tackle the exploitation of increased volumes of distributed data given progress in computer networking and communication strategies. Pragmatically, an improved ability to foster '*workable linkages*' (Parks 1993, p33) between modelling system modules fostered by greater openness in proprietary GIS (e.g. ESRI Map Objects™) has led to case by case solutions (e.g. Downs and Priestnall 1999). Surprising as it may now seem, this was a major area of GIS development that many senior figures failed to foresee at an early stage (e.g. Goodchild *et al.* 1991) as Longley *et al.* (1999) comment in their introduction to the revised *'Geographical Information Systems'* (1999). Earlier work skirting around this subject rather dwelt on the need for data standards and 'stand-alone' protocols for format translations between software vendors (e.g. Wright *et al.* 1998).

On the second issue, the degree to which spatio-temporal simulation functions should be adopted as intrinsic GIS functions is a matter of some debate (e.g. Maidment 1993) although the development of more generic dynamic modelling systems within GIS has been the focus of attention over the past few years (e.g. Leavesly *et al.* 1993, Wesseling *et al.* 1996, Takeyama and Couclelis 1997, Park and Wagner 1996, Westervelt and Hopkins 1999). The majority of these examples are raster oriented 'cellular automaton' based approaches however (Park and Wagner 1997, Takeyama and Couclelis

1997, Van Deursen 1995), despite their potential scale-related disadvantages for practising integrated modelling. From the above discussion, their similarities of data structure to typical raster GIS and the availability digital data sets with conforming structure (e.g. digital terrain grids) confer immediate if short term advantages. Indeed, many (e.g. Heuvelink 1998, p6) still suggest that the problems of environmental science are more suited to the field approach than an object interpretation. Continuously varying factors such as soil moisture for example do not lend themselves well to object categorisation, even accounting for the fact that objects may themselves have uncertain boundaries. In the case of work at Utrecht, the development of a dynamic modelling system (van Deursen 1995, Wesseling *et al.* 1996) was facilitated by full access to the underlying structures of the in-house GIS, so avoiding many of the problems regarding openness at the time. Given the enormous range of subject areas making use of GIS, it is arguable whether a 'core' modelling functionality can be defined. Indeed, as Maidment (1993) questions, should any attempt be made to carry out environmental modelling within a GIS framework? Of the environments listed for example, only Westervelt and Hopkins' (1999) appears to have components that a multi-actor population model in space-time (e.g. insect/crop relations and populations) would require.

2.3.2 Data issues: Interpolation

Interpolation is an underpinning element in many applications within the environmental modelling/GIS literature, owing to the point nature of historical climate records in particular that are a feature of much ecological and hydrological based work. As such, discussion of the relative merits of interpolation techniques forms substantial portions of both standard textbooks within spatial analysis (e.g. Unwin, 1981) and more recently GIS (e.g. Burrough and McDonnell 1998) in addition to journal and conference literature (e.g. Lam 1983). Despite the heralding of many new techniques over the years however, and the oft-made claims of proponents of kriging, there remains no 'best' universal interpolator (Myers 1994): any recommendations are critically dependent on the underlying data. For this reason, emphasis is placed here on a summary review of the major classes of interpolation techniques found within the literature, especially but not exclusively those previously found satisfactory for creating temperature surfaces. Exhaustive comparisons between techniques are prohibited by sheer variety within the context of this broader ranging research effort. Discussion is constrained to point, rather than area, interpolators. Long established techniques, such as inverse distance weighting or polynomial interpolating regressions (trend surface techniques) need little introduction. Rather, discussion focuses on the kriging and splining families of functions commonly found within applied environmental studies together with an introduction to more recent concepts such as conditional simulation and interpolation by neural networks.

Drawing upon and extending the wide ranging reviews of Burrough and McDonnell (1998), Lam (1983) and Mitás and Mitásová (1999) in particular, an updated general review of interpolation techniques is found within Appendix 3. This has been amended to incorporate changing perspectives on the relative advantages and disadvantages of particular techniques over the past ten to fifteen years and incorporate more recent methods. Criteria for selecting the most appropriate technique (e.g. visual impression, mathematical accuracy, mathematical/computational complexity, availability of software and level of automation (Franke 1982a) however remain unchanged. It is interesting also to reflect on changes of perception, especially regarding views on uncertainty within interpolation results. Lam (1983) for example interprets the possibility that alternative solutions for the same data set which may occur when building trend surfaces as a disadvantage. This in contrast provides the very rationale behind the growing use of conditional simulation today. Similarly, while exactness in honouring points has been viewed as an advantage in the past (Lam 1983, Burrough 1986) and is still presented within McDonnell and Burrough (1998 p102) as an advantageous feature, inexactness is now accepted in a number of application areas to reflect more realistically data uncertainty and measurement error (e.g. Hutchinson 1993b).

The impact of increased computing power has provided more opportunities to explore alternative interpolators. What may have been computationally infeasible 15 years ago in applied studies (e.g. kriging/co-kriging multiple surfaces) is no longer the case. Rather, it is for example the latest developments in conditional simulation that may, in the absence of access to a Cray computer, prove impractical: parallel-computing strategies for interpolation (e.g. Armstrong and Marciano 1997, Luh *et al.* 1997) form a further new tranche within the literature. Also reflecting these changes in computing capability, Mitás and Mitásová (1999) add to their list of desired functionality in an interpolation scheme the need for multi-dimensional formulation and applicability to large data sets.

Predominant within the applied GIS scene is a greater use of statistical knowledge (e.g. geostatistics) to provide more sophisticated analyses. Statistical approaches to old problems however, such as the selection of the best radius or number of points with which to apply inverse distance weighted interpolations, are surprisingly uncommon and their omission from mainstream packages (e.g. SURFER, ARC-INFO GRID) fails the naive user. The more complex automatic fitting of variograms as part of the kriging process, a practice vehemently challenged by purists (e.g. Deutsch and Journel 1992) and one of considerable on-going research (e.g. Barry and Ver Hoef 1996, Lamorey and Jacobson 1995, Genton 1998), is in contrast implemented as a standard pragmatic procedure within ArcInfo™. Debate has shifted to issues of desirability of standard techniques rather than their computational practicability. In their recent review of interpolation techniques, Mitás and Mitásová (1999) suggest this area will be an important focus for future research. Arguably, many previous comparisons between techniques have been biased by the user setting arbitrary parameters apriori. This study will use automatic parameter fitting for the fitting of all interpolation parameters and techniques incorporated for both consistency and, primarily, adaptability.

Geostatistics have been applied to a wide body of environmental data (e.g. Cressie 1993, Rossi *et al.* 1992). Central to kriging techniques is the minimising of the variance of interpolation error, for which a variogram fitting process is critical. Ordinary kriging is more widely applied than universal kriging or co-kriging, unfortunately however often without first examining the data for underlying trends (e.g. Bolstad *et al.* 1998) or using inadequate volumes of sample data (e.g. Nalder and Wein 1998). Webster and Oliver (1990, p222) for example suggest that upwards of 100 data points are required for modelling the spatial semi-variance, the most critical process within a kriging analysis. Universal kriging has the advantage of incorporating local trends within the interpolation process, while co-kriging uses cross-covariances between point data sets to guide the interpolation process: for ordinary kriging, trend must be removed in advance. Where the correlation between dependent and independent variables is strong and linear, the literature recommends universal kriging while where it is non-linear, the co-kriging has more theoretical weight. In practice, co-kriging rarely appears to outperform its counterparts, especially where primary and secondary variables are co-located (e.g. Goovaerts 1998). Its potential benefits appear not to outweigh the additional computational complexity involved, although the use of Fast Fourier Transforms to compute variograms or positive definite covariance tables appears to be a new development in simplifying the procedure (e.g. Marcotte 1996, Yao and Journel 1998). Disjunctive kriging provides a spatial perspective on the probability a specified threshold is exceeded: particularly useful when assessing pollution issues, from critical loads to nitrate leaching (Finke 1993).

Spline functions of varying complexity have been applied to interpolation tasks, the simpler of which are best applied for visualisation purposes rather than modelling tasks (Burrough 1986). Thin plate spline functions provide a number of advantages when modelling surface form (Mitásová and Hofierka 1993), and in particular may be extended to incorporate linear covariates (partial thin plate splines). In simple terms, they may be visualised as a tense sheet stretched between sample points such that the surface form is an energy minimising compromise between maximising smoothness while honouring the individual data values. Use of splines with multiple independent variables (e.g. x,y and elevation), as opposed to the two primary independent variables (x and y) plus linear covariates (e.g. elevation), is analogous to co-kriging although splines are optimised by maximising smoothness while avoiding unacceptable levels of residual fit. 3d partial thin plate splines have been found beneficial when modelling frost hollows (e.g. Laughlin *et al.* 1993) and in a re-modelling of Dubrule's (1984) soil properties data set (Hutchinson and Gessler 1994). Hutchinson's form of partial thin plate spline (ANUSPLIN, Hutchinson 1991b) has been used primarily to model climate (1991, 1993, 1999) and terrain (Hutchinson and Gallant 1999). The ability to specify apriori the reliance to be placed on certain data points (Hutchinson 1995) is a particular strength of Hutchinson's method as applied to long term climate data. Mitás and Mitásová (1991, 1999) extend this form to a regularised tension spline: a more mathematically sophisticated form of thin plate spline incorporating an extra derivative function to improve surface continuity. Continuing with the steel plate analogy, Mitasova and Mitas (1994) explain that this allows the interpolation to be tuned from thin plate to a more adaptive membrane. This has enabled the extension of the interpolation scheme to four dimensions without serious discontinuities arising, and has allowed the multi-temporal modelling of pollutants and stream flow within the context of GRASS (Mitásová *et al.* 1995,1996).

Surprisingly, relatively few comparisons in applied studies between thin plate splines (deterministic) and kriging (stochastic) exist, and historical divisions between the stochastic and deterministic research 'camps' have tended to polarise opinion between the kriging and splining families of techniques. Such differences have been settled with the evidence that the dual form of kriging has strong connections with both splines and radial basis functions (e.g. Myers 1994, Hutchinson and Gessler 1994, Mardia *et al.* 1996). The kriging family retains the greater flexibility within the interpolator since the order of derivative is usually set *ad hoc* by the spliner. In contrast, in kriging the order of the derivative may be set independently of the covariance function (Hutchinson and Gessler 1994). Laslett (1994) in a study of soil pH found that splines never outperformed kriging (universal), although their performance could be matched when interpolating regular data. In the case of irregularly spaced data, kriging outperformed splining. This is perhaps attributable to the ability of kriging to account for the local geometric configuration of points when computing interpolation weights while splining relies on distance functions alone. Other systematic comparisons between kriging and partial thin plate spline interpolation are rare within the literature, and no previous examples of the differences between the results of the two methods for the interpolation of daily maximum and minimum temperatures have been found.

Splining has been criticised on the grounds that no fully spatial error surfaces may be fitted, unlike the case for kriging where the spatially continuous variance of the estimate may be mapped. However, using Bayesian assumptions similar to those of kriging, Whaba and Wendleberger (1980) and Silverman (1985) have shown that prediction standard errors may theoretically be computed for spline equations: Hutchinson (1998) provides a practical demonstration of such continuous surfaces in his recent interpolations of daily Alpine rainfall. Similarly to the kriging variance however, these surfaces account for the distribution rather than value of errors, restricting their utility in a study such as this. Other explorations of uncertainty within spline functions may also be found within the mathematical literature, for example in explorations of fuzzy interpolators (Kaleva 1994), but these are rarely applied within a GIScience context: defining appropriate membership functions provides a considerable practical barrier to their use in an applied context such as this.

Of the newer techniques now being applied to interpolation, perhaps most significant is the increased body of research into condition simulation (e.g. Pebesma and Wessling 1998, Journel 1996, Englund 1993, Rossi *et al.* 1993) which provides the user with multiple equally probable surfaces based upon both the variogram and the overall statistics of the data. A variety of algorithms have been developed, the most commonly used being the sequential Gaussian method (Atkinson 1999). Conditional simulation has been used to estimate insect populations (Rossi *et al.* 1993). However, this did not use any guiding variables or the fitting of an initial trend model as might be expected given the large area (225 by 150km) of the study. In the context of this thesis where multiple interpolations are required, the computational intensity of conditional simulation rules out its use for the interpolation of daily maximum and minimum temperatures without associated considerations of parallel computing technology. A further body of work, in a move away from the statistical constraints of geostatistics, draws upon developments in the artificial intelligence community to improve interpolations (e.g. Dowd 1994, Pariente 1994, Rizzio and Dougherty 1994, Cheeseman 1998). Neural network approaches for example vary from those essentially mimicking standard polynomial regression or trend procedures (Dowd 1994, Cheeseman 1998), to those that incorporate local data configurations (Rizzio and Dougherty 1994, Pariente 1994).

In addition to the question of most appropriate interpolator a commonly implicit thread within the literature is that addressing the issue as to whether it is best to interpolate the inputs or outputs from an environmental model (Figure 2-8). Most environmental models take as their input a sequence of parameters that are observed at only a limited number of points. There are many practical circumstances in which one wishes to extend these models to make spatially continuous predictions. Many ecosystem models for example are driven by climatic variables that are highly dynamic over time (Cramer and Fischer, 1996) but for which data is sparsely distributed over space. If we wish to run an ecosystem model over space, do we first need to estimate how values of each input variable to the model may change in relation to the changing environment away from (e.g.) meteorological stations? Alternatively, might the ecosystem be equally well represented by running the model at locations only where the condition has been directly observed and then interpolating the modelled results to create a continuous surface? This shows how the question (shown pictorially within Figure 2-8) arises practically in many applications where dynamic modelling requires spatial data inputs, including fire management, hydrological, crop yield, pest risk and nutrient transfer models (e.g. Kessell 1996, Landau and Barnett 1996).

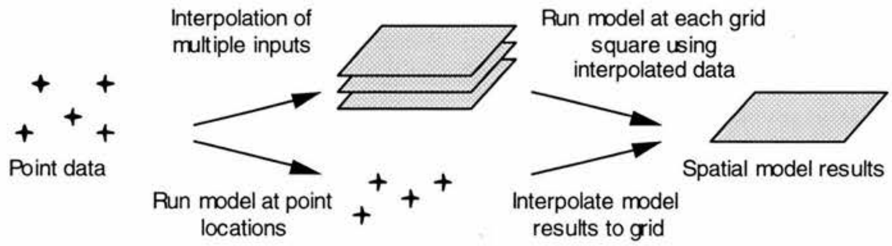

Figure 2-8. Interpolate inputs or outputs?

Occam's Razor suggests that the simplest approach is the most appropriate, and unless unacceptable model estimations may result, may explain the continued preference for the less intensive tactic of interpolating one set of model results rather than multiple model inputs. However, this question posed has rarely been considered explicitly within the published GIScience literature. Viewing the issue in terms of error propagation, Burrough (1992) suggested that the question could be solved using fully spatial multiple simulations, challenging this status quo. For applied scientists already frustrated by practical difficulties in the management of data and computational performance of current proprietary GIS when modelling in space-time (e.g. Johnston *et al.* 1996), this may be considered impractical. For both practical and intellectual reasons therefore, in applied studies a decision to interpolate model outputs rather than inputs has often been made. The application area for this case study, that of pest risk analysis, exemplifies this situation (e.g. Bolstad *et al.* 1996, Régnière 1996, Schaub *et al.* 1995b) with the majority of previous workers choosing to run a model at data points and then interpolate the results to a surface.

Outside the mainstream geographical science literature, consideration of whether to interpolate model inputs or outputs has occasionally been tackled. A recent thread within the '*Hydrology and Groundwater*' on-line discussion list (Ferreyra, March 1998) highlights the currency and unresolved nature of the issue. Within the published literature, soil scientists working with a cadmium sorption model dependent on pH and organic carbon content (Bosma, 1994) term the problem the 'IC/CI' (interpolation followed by calculations, calculations before interpolations) debate. This work suggests that for relatively small data sets a CI procedure performs better than an IC procedure on the basis of mean square error (m.s.e.) but at the expense of over-smoothing the data. Both results reverse with additional base data. Interestingly, over a full model run the m.s.e. results of both IC and CI were similar whatever the data volume. Data volume was more important than the impact of interpolation order in terms of improving overall modelling accuracy. Stein *et al.* (1991) showed by a small margin in terms of mean square error of soil moisture that the CI approach was preferable, but that the outcome also depended on the interpolation procedure used. Contributing to the on-line discussion, several scientists suggested that where the function linking inputs and outputs is linear there would be no difference between the approaches. This hypothesis does not however appear to account for day-to-day fluctuations in underlying temperatures, whether linear or not. Even where the linking functions are broadly linear (as for example in a simple accumulated temperature model) the spatial pattern of temperatures will change daily according to synoptic considerations. Such comment highlights the lack of emphasis on space-time considerations, sources of error and error propagation functions to date. These are issues that will be explored further in chapter 6.

2.3.3 Data issues: Interpolation of climate data

2.3.3.1 Introduction

The interpolation of climate or weather variables plays an underpinning role in many geographical models of natural and agricultural systems (e.g. Running *et al.* 1987, Landau *et al.* 1998, Semenov *et al.* 1996, Goodale *et al.* 1998). Surprisingly, relatively few studies focus upon the interpolation of continuous national coverages of daily temperature using now familiar geostatistical or splining techniques, although a more recent upsurge of interest may be detected (e.g. Landau and Barnett 1996, Cornford 1997). More often within applied studies, long established and mathematically simpler methods such trend surface analysis (e.g. Russo *et al.* 1994, Goodale *et al.* 1998), inverse distance weighting (e.g. Supit *et al.* 1998) or vertical lapse rates (e.g. Aber and Federer 1992, Running *et al.* 1987) are used. However, in relation to the goals of this particular project, insect phenologies are highly sensitive to daily maximum and minimum temperatures (e.g. Morgan 1992). This sensitivity warrants a greater focus on techniques for the interpolation of maximum and minimum daily temperatures than has previously been found, since there is a strong possibility that multiple small input errors may compound to significant effect.

In order to provide a context for discussion of previous interpolations of temperature, and in particular the shift in this work from annual or monthly temperatures to those on a daily basis, the nature of British climate requires brief mention. It is commonly said that *'... the British Isles have no climate, but merely weather'* (e.g. Manley, 1970). This suggests that consideration of synoptic situation when interpolating *daily* variables as in this study, either implicitly in terms of flexibility within the methodology or explicitly by incorporation of weather type classification, may prove critical. A number of synoptic classification schemes have been developed that are applicable in a British setting, from the long standing but arguably subjective (e.g. Lamb's classification) to more recent automatic schemes (Mestre 1997, Jones *et al.* 1993).

2.3.3.2 Interpolation of temperature: review

Interest in global process, especially in relation to changing climate, has resulted in several global climatologies (e.g. Leemens and Cramer 1991, New *et al.* 1998). Supplementing these are further global, continental and regional experiments (e.g. Hulme and New 1997, Hutchinson 1991b). Accounting for the earth's curvature forms an important element within the work spearheaded by Willmott (e.g. Willmott and Robeson 1995, Willmott and Matsuura 1995, Legates and Willmott 1990) but is surprisingly absent from much other global and continental work (e.g. Hutchinson, 1991b). Of particular relevance to this British based study is the more recent work of these schools, which focuses on improving interpolation accuracies using gridded 'guiding variables'. Willmott and Robeson, for example use long term averages to guide their inverse distance weighted method, and suggest that time-averaged information *'... should also improve spatial interpolations of climate variables at smaller spatial scales.'* However, these cannot resolve spatial differences between period caused by differences in synoptic situation. Perhaps more preferable is the interpolation of anomalies (e.g. Jones *et al.* 1986a,b) which might be expected to be considerably smoother than the raw data. In areas where errors are high, this should have the effect of dampening variance in the results. With the advent of global and regional digital elevation data elevation has also, and more significantly in terms of accuracy, been used to guide interpolation (e.g. Leemans and Cramer 1991, Willmott and Masuura 1995). Willmott and Masuura for example achieve a 24% increase in accuracy with the inclusion of height data.

At a monthly time step and regional spatial scale, Hutchinson's (1991b) partial thin plate splines dominate the literature. Their ability to incorporate 'guiding' variables within the interpolation procedure and to account for variation in temporal means for partial temperature records (e.g. New, Hulme and Jones, 1998) make this technique highly favourable. European monthly climate normal interpolations produced by Barrow *et al.* (1993) using partial thin plate splines for example form a base for many climate change studies. During the development stage of Barrow's climatological study, the performance of an UNIRAS average inverse distance weighting/quadratic smoothing procedure was compared against partial thin plate spline techniques but found lacking: no exploration of other geostatistical methods such as kriging was made. This may reflect potential problems meeting the stationarity requirements of kriging over large expanses. At a monthly level but national extent however, universal kriging has been used for interpolating January long term mean air temperatures throughout Scotland (e.g. Hudson and Wacknagel, 1994). The later study showed co-kriging to have no particular advantages over kriging with external drift (elevation), but rather to simply introduce additional computational intensity. The authors noted strong differences in the direction of drift from previous studies that used normals for July, suggesting that standard topo-climatic indices such an unvarying lapse rate should not be used without some means to accommodate variation throughout the year. This concurs with comments from others such as Cramer (Cramer and Fischer, 1996) who now consider their early use of fixed lapse rates (e.g. Leemans and Cramer 1991) inappropriate. Holdaway (1996), in a North American study, draws attention to the need to account for major trends caused by topographic features at this monthly scale. Currently, the use of elevation to guide the interpolation of monthly temperatures is now de facto, although there is a mix between trend surfaces, splining and some kriging methods as indicated with Table 2-5.

Table 2-5. Techniques used for interpolating monthly mean and 'normal' temperatures

Paper	Spatial scale	Temp. scale	'Best' technique	Techniques explored
Barrow *et al.* (1993)	10 km^2	Monthly anomalies	3d partial thin plate splines (lat., long. and elevation)	UNIRAS IDW, partial thin plate splines
White and Perry (1989)	10km^2	Quarterly	Polynomial regression (Multiple topographic indices)	Polynomial regression
Hudson and Wackernagel (1994)	5km^2	January mean normal	Kriging with external drift (elevation)	Kriging with external drift
Hutchinson (1991b)	2.5km^2	Monthly normals	Partial thin plate splines (elevation, coast)	Partial thin plate splines
Daly *et al.* (1994)	4km^2	Monthly averaged maxima and minima	Local regression (topographically similar 'facets')	Local regression
Goodale *et al.* (1998)	1km^2	Monthly averaged maxima and minima	Polynomial regression (elevation)	Polynomial regression, modified IDW
Holdaway (1996)	5km^2	Monthly means	Ordinary (de-trended) kriging (elevation and lake effect)	Ordinary kriging, de-trended ordinary kriging
Lennon and Turner (1995)	5km^2	Monthly mean climate normals	Partial thin plate splines (multiple covariates)	Partial thin plate splines, polynomial regression, UNIRAS IDW
Pielke and Mehring (1977)	5km^2	Monthly means	Linear 'lapse rate' regressions	Linear 'lapse rate' regressions
Nalder and Wein (1998)	Not specified	Monthly normals	De-trended inverse distance weighting ('GIDS')	De-trended IDW ('GIDS'), ordinary kriging, co-kriging

Earlier regression based work (e.g. White 1979) which used multiple topographic factors to model temperature has been criticised for its lack of validation (Gregory 1983). However, studies such as

Holdaway's (1996) indicate a resurgence of interest in using topo-climatic data to guide interpolation. Techniques developed for use with precipitation data (Daly *et al.* 1994, *PRISM*) using topographical 'facets' are now being used to model temperatures (Patterson, 1998). In the case of *PRISM*, a local regression function is weighted according to similarity of location, elevation and topographic position. The *AURELHY* method (Mestre, 1997) uses local principal components of topography as guiding variables: arguably, more impenetrable in terms of process. In a British context, these developments are best illustrated at the monthly time step in the British work of Lennon and Turner (1995) who incorporated a variety of topo-climate based linear sub-models within a partial thin plate spline context. Chapter 4, and research carried out in parallel by Cornford (1997), owes much to their approach.

Table 2-6. Methods used for the interpolation of daily mean, maximum or minimum temperatures (✓), with 'best' technique (✔)

	Collins and Bolstad (1996)	Landau and Barnett (1996)	Laughlin *et al.* (1993)	Van de Voet (1994)	Blennow and Persson (1998)	Bolstad *et al.* (1998)	Cornford (1997)	Ishida and Kawashima (1993)
Multi-dimensional nearest 'similar' neighbour				✔				
Polynomial/trend regression	✔	✓			✔	✔		✓
Inverse distance weighting	✓	✓						
Ordinary kriging	✓	✔					✓	✓
Co-kriging	✓							✔
Partial thin plate splines			✔					
Cubic splines	✓							
Lapse rate methods	✓		✓			✓		

Turning to the literature reporting the interpolation of daily meteorological data from synoptic stations, Collins and Bolstad (1996) compare a variety of interpolation techniques for daily maximum and minimum temperatures over the Appalachian range. Their conclusions suggest polynomial regression (trend surface + covariates) appears preferable over other local techniques such as inverse distance weighting. In a study of greater depth for the same area (Bolstad *et al.* 1998), second-degree trend models (including elevation, termed 'regional' regression) were found superior to both kriging, regional (Voronoi determined) and local lapse rate models (empirically determined). The trend model also accounted for relationships in the data between successive days. Whilst their treatment of regression was strong however, the geostatistical treatment was less robust; stationarity assumptions were ignored despite the probability of drift in an area of highly variable terrain. Practical problems with kriging, owing to a lack of automation at the variogram-modelling phase, also led the authors to dismiss the technique. In contrast, Ishida and Kawashima's (1993) study interpolating daily means derived from the Japanese synoptic records over a limited area to a resolution of 250m but with consistent treatment of elevation between regression, kriging and co-kriging methods, shows a preference for co-kriging. Bolstad *et al.* 's (1998) paper stands however as a useful discussion of the over-reliance on lapse rates and impact of synoptic conditions when modelling at the daily scale. It also concludes that there is a need for greater consideration of topo-climatic factors, either in the form of terrain shape or by improved consideration of cold air drainage effects and exposure related increases in maximum temperatures.

Using a similar data set to that available for this study, Landau and Barnett (1996) demonstrate the feasibility of producing national daily interpolated temperature surfaces for England and Wales. The applied agricultural context of that study lends it certain similarities to this, although the range of climatic variables is wider, at the expense of topographic and synoptic detail. Based on the assumption that '*... there is no reason to believe that an underlying trend changes rapidly or discontinuously between days. In particular, the underlying trend might well be the same for every year given a particular date*', a trend surface was fitted to the daily time series for each known site using seven years of data. This is used to extract the residuals for interpolation, in that case using kriging. In streamlining the number of parameters to model, and the complexity of the process, this approach has much to offer. However, when considering the variability of the underlying meteorological processes from day to day and between years that have been identified as a confounding set of factors by other researchers (e.g. Bolstad *et al.* 1998, Cramer and Fischer 1996, Holdaway 1996, Cornford 1997) the underlying assumptions of temporal uniformity would seem questionable. Lapse rates, for example, are known to fluctuate seasonally while differences in weather system and air mass direction cause different processes, such as katabatic or Föhn winds, to occur under certain conditions only. This study also has limitations that arise by disregarding processes, for example by using third order elevation variables within the trend surface equations when linear lapse rates are well rehearsed both empirically and through the laws of physics. Similarly to Bolstad *et al.* (1998), Landau concludes that more detailed consideration of topo-climatic influences (in this British case, an urban index and measure of proximity to coastal areas) would considerably improve results for daily temperature estimations over wider areas. Since the variability of weather data is known to have a strong influence on pest development, Landau's method, while economical, appears undesirable in the context of this study.

Noting an apparent need for improved consideration of topo-climate when interpolating daily temperatures, Cornford's (1997) primary focus in interpolating winter minima over Britain was placed on improving the set of gridded data used to guide interpolation by ordinary kriging. Unlike previous work, a cold air drainage model formed the crux of this approach to improve the incorporation of topo-climatic influences in conjunction with the consideration of other factors such as urban heat islands, terrain variability and land cover. Contrary to the findings of Bolstad *et al.* (1998) local regressions between temperature and gridded variables were not found superior to global models, perhaps because of the wider range of locally detailed explanatory variables. This provides some support for White's (1979) decision to use spatially invariant regression models, a study much criticised by Gregory (1983) on this basis. Cornford's work, along with that of Lennon and Turner (1995), considerably advances the move towards greater consideration of topo-climatic factors when interpolating daily or monthly temperatures. Results from Lennon and Turner also hint that the choice of guiding variables may be more critical than interpolation technique, where multiple variables are considered. These ideas will be explored further within this study.

Table 2-7. External variables used to assist with interpolation

	Collins and Bolstad (1996)	Landau and Barnett (1996)	Laughlin *et al.* (1993)	Van de Voett (1994)	Blennow and Persson (1998)	Bolstad *et al.* (1998)	Cornford (1996)	Ishida and Kawashima (1993)
Terrain								
Height	✓	✓	✓	✓			✓	✓
Roughness							✓	
Cold air drainage								
Sky view						✓		
Land cover							✓	
Urban effect							✓	
Distance to water				✓			✓	
Vegetation							✓	
Soil								

At all of the spatial and temporal scales reported within the literature on interpolating temperature data the use of external gridded data, whether through treatment as 'external drift', de-trending or co-kriging, markedly improves the results of interpolation. Indeed, Mitás and Mitásová (1999) identify the next generation of interpolators as those better incorporating knowledge of the underlying geographical processes. However, Grayson *et al.* (1993) in their somewhat grim assessment of progress in linking process models with GIS for hydrology and the selection of parameters used in that context, caution that:

> *"... information content can only be increased by interpolation if underlying relationships are present and can be defined.*
>
> *For topography based interpolations, it is therefore vital that topography is related to the dominant hydrological processes in the particular management situation. The modeller who fails to realise these subtleties will misinterpret the results and place greater confidence in the spatial variability of model output than its underlying performance justifies."*

While made in the context of hydrological modelling, the underlying theme of this statement is generic within geography as a whole: the need to identify and understand the scale at which process is acting. Within the context of creating gridded climatologies, with the exception of work by Cornford (1997) explicit consideration of underlying climatological processes has been slow to emerge. Even Lennon and Turner (1995), who took into account a wide selection of topo-climatic factors, confess that:

> *"We suggest ... that possibly the selection of independent variables a posteriori from the empirical knowledge of the causes of atmospheric temperatures, rather than our a priori set of conveniently obtained topographic variables, might produce some further improvement."*

The payoff between improved topo-climatic modelling and theoretically more complex interpolation however remains poorly explored. This study, interpolating daily maximum and minimum temperatures throughout the annual cycle, therefore contains two major methodological elements: a limited topo-climatic study and a subsequent exploration of the differences in estimation accuracy provided by a variety of interpolation methods. The empirical nature of topo-climatic modelling as distinct from the modelling of non-linear climate processes at multiple atmospheric levels using physical laws (e.g. Running *et al.*, 1987, 1996) inevitably remains a potential point of contention for theoretical purists. However, previously use of partial thin plate spline interpolation by those more commonly associated with process-based studies (Laughlin and Kalma 1990, Laughlin *et al.* 1993), supports the working approach. This is particularly the case given the applied context of this project.

2.3.3.3 Topo-climate: review

Reviewing the latest edition of Geiger's 'The climate near the ground', Fritschen (1997) notes the beginnings of an upsurge of interest in topo-climate following a slump during the 1960s. To some measure, this reflects the wider return to positivist approaches to geography engendered by the increased availability of digital data sets and GIS tools with which to model tasks previously perceived as computationally over-complex. The dominant topo-climatic effects on maximum and minimum temperature may be divided into two main categories: those relating to terrain and those resulting from differences in land cover characteristics. These components are widely discussed within climatology texts (e.g. Barry and Chorley 1982, Henderson-Sellers and Robinson 1986, Oke 1987), and are summarised within Table 2-8 below.

Table 2-8. Local climatic effects

Land cover	Topography
Net radiation absorbed	Adiabatic cooling
Internal boundary layers	Drainage and evaporation on slopes
Surface roughness	Local winds caused by the above
Urban heat effects	Sea breezes
	Variation of solar radiation received
	Descent of air from mountains (Föhn effect)

The influence of elevation on temperature (the adiabatic lapse rate) is dominant and the importance of this pressure-based effect is reflected in its wide use within interpolation studies (Table 2-7). Cold air drainage has a more occasional but significant effect in agricultural terms since this is the primary cause of night frosts during critical periods of the growing season, and considerable effort has been made to model its ponding both using process models (Laughlin and Kalma 1990, Avissar and

Mahrer, 1988) and more empirical approaches (Laughlin *et al.* 1993, Blennow and Persson 1998). Bolstad *et al.* (1998) point to consideration of cold air drainage in particular as being needed to improve their interpolations of daily temperatures. The separation of climate effects within Table 2-8 is in many senses artificial, since the movement and generation of cold air will itself also be affected by land cover and surface roughness as Cornford's (1997) model exploits.

A further material effect on daily temperatures, especially within a British context, is that of urban 'heat islands'. Both Landau and Barnett (1996) (daily temperatures) and Lennon and Turner (1995) (monthly temperatures) acknowledge their omission of this factor was significant and might provide an explanation for their largest residuals. Accounting for the effects of sea breezes again provides an added complexity for British studies given the strong maritime influence on temperature (e.g. Landau and Barnett 1996). The strong variability of coastal breezes effect owing to season and weather pattern provides a strong impetus for surrogate modelling techniques to model this factor using simple directional variables.

Summarising his wide range of potential guiding variables used for modelling daily winter minima at a resolution of $500m^2$, Cornford (1997) also suggests that distance to the nearest drainage feature, land cover derived radiative properties, tree cover and the difference between cell elevation and maximum within 5km (local cold air ponding) are significant. This list itself highlights the importance of spatial scale in relation to underlying physical processes when modelling topo-climatic parameters. This issue is explored in greater detail within the methodology (Section 3.3.2, p94).

It is interesting to note in this context that previous proponents of physical models for determining minimum temperatures (e.g. Laughlin and Kalma 1990) have themselves turned to interpolation to improve their results (e.g. Laughlin *et al.* 1993). This leads to the suggestion that a balance between the two approaches that is compatible with physical processes but that also draws more heavily on auto-correlation than work which focuses heavily on de-trending data before for interpolating (e.g. Cornford 1997) might provide practical advantage.

2.3.4 Uncertainties and the computation of spatially distributed error

Discussions regarding error and uncertainty have formed a significant portion of the GIS research literature over the past five years. Taking the *International Journal of Geographical Information Science* as a benchmark, this is a trend that shows few signs of abatement. However, often the treatment of such issues is narrow. Writing in the context of climate change research, Henderson-Sellers (1996) observes that '*Phrases like "the uncertainty in the scenarios" appear to carry meaning but the information seems to be, at best, incomplete and, at worst, totally debased by multiple definitions and usages* (sic).' The term 'uncertainty' encompasses prejudices, perspectives, incompleteness of information, as well as the differences in completeness, accuracy and sensitivity of different forecasting tools, as Van Asselt *et al.* (1996) identify in their taxonomy of uncertainties

(Figure 2-9).

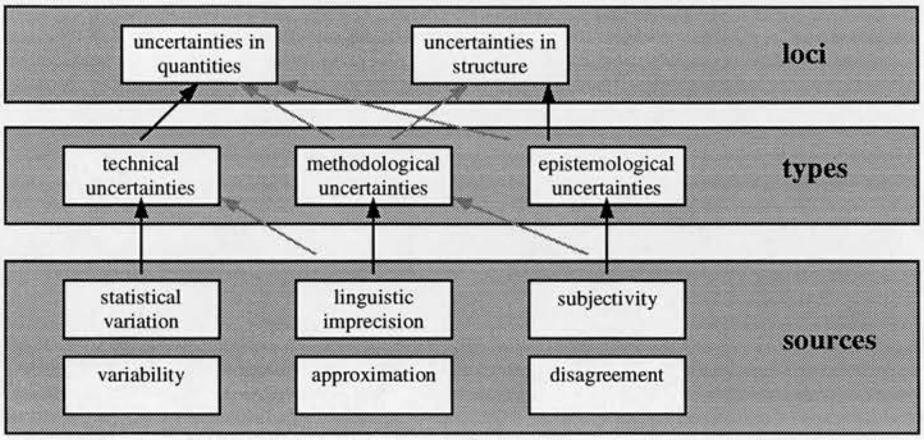

Figure 2-9. Taxonomy of uncertainties, after Van Asselt *et. al,* (1996)

Although, unlike Van Asselt, the focus for this study is not climate change but rather pest risk assessment, many analogies may be drawn. In an approach framed around GIS such as this there is a danger in focusing on the more tangible technical contributions to uncertainty: particularly those within the geographical element of the study. Quantification has the effect of implying 'completeness' of treatment regarding uncertainty. The common GI Science goal, to provide standard error bars or error surfaces, as illustrated by Heuvelink (1999), Mitásová *et al.* (1995) or Hutchinson (1999) is a helpful contribution for potential users of the results. However, it does not cover questions regarding the modelling of phenologies rather than populations for pest risk, or debate regarding the wisdom of climatological determinism (Davis *et al.* 1998) for such a purpose.

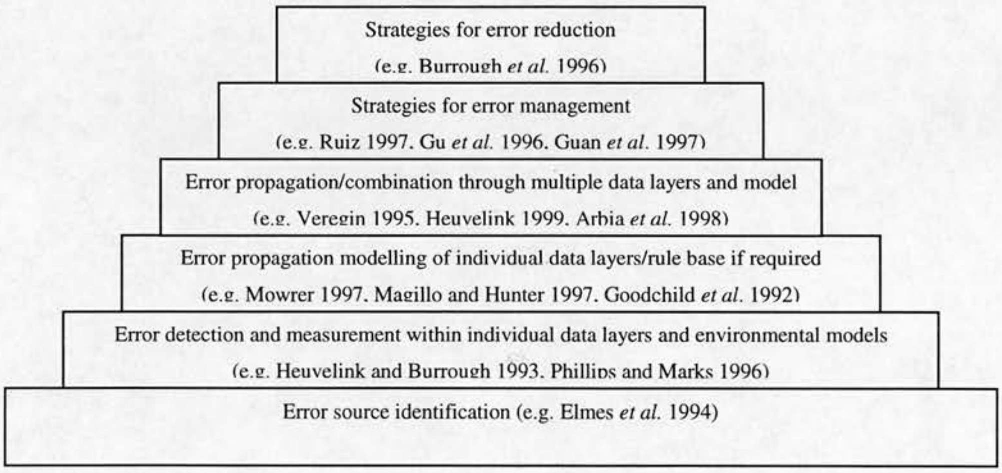

Figure 2-10. Hierarchy of needs for modelling error in GIS operations (Expanding and updating upon Veregin, 1989)

Circumspect in his use of the phrase 'data quality', Veregin (1999) in a GIScience context provides a typology veering towards that of Figure 2-9. He identifies the error categories accuracy (positional/attribute/temporal), consistency and completeness of data. Of these classes, the term 'completeness' can be construed to incorporate methodological uncertainties within modelling approaches in addition to concepts regarding identifiable errors of omission within datasets. Deeper considerations of ontology, and in particular the definition and division between of phenomena according to purpose, also arise as a natural form of uncertainty within object–oriented modelling (e.g. Livingstone and Raper 1994) and as a consequence of geographical scale (Openshaw and Alvanides 1999). Pickles' (1995) collection has also opened up more explicit consideration of differences of worldview within GIScience, drawing epistemological uncertainties (Figure 2-9) into discussion. Many others in GIScience purporting to consider uncertainties however (e.g. Fisher 1999) in fact focus upon 'error' issues.

Drawing upon Veregin's original hierarchy of needs (1989) but extending and exemplifying the concept, it is clear that before considering error propagation in more detail, individual data or modelling errors must first themselves be identified and modelled (Table 2-10). Within environmental error analysis, as distinct from the database quality literature, work has largely concentrated on assessing quantitative attribute errors at the expense of the other major categories (Table 2-9), although positional error is occasionally modelled (e.g. Stanislawski *et al.* 1996, McKenney *et al.* 1996). Both Elmes *et al.* (1994) and Heuvelink (1998, p6) for example expressly omit consideration of positional or qualitative/categorical errors, arguing that they are of only minor importance for environmental applications. Considerations of geometric quality and relative spatial arrangement within digital terrain models provide an important exception to this generalisation (e.g. Monckton 1994, Brown and Bara 1994). In contrast, there has been a strong historical bias within the general GiScience literature on considerations of qualitative, logical (e.g. Huang *et al.* 1992, Lanter and Veregin 1992) and positional (e.g. Shi 1998) inaccuracies. In the case of the latter, classic examples include those arising from generalisation and digitising (e.g. Blakemore 1983) and often used the 'epsilon band' concept. As Veregin (1999) notes, just as time has been a neglected axis in modelling, temporal error has similarly received little attention within models of spatial data accuracy. In general, temporal error is conceived in terms of currency (Thapa and Bossler 1992), considering issues such as the relative decay in accuracy over time of different data sets and the consequent appropriateness of their continued widespread use. Defining objective time scales themselves pose certain barriers: is time linear, as Peuquet (1994) for example assumes, or circular (timetables, annual cycles), or relative? This is an issue that will be considered further within the methodology in an agricultural context.

Table 2-9. Standard components of error

Component
Attribute accuracy (e.g. Heuvelink 1998)
Positional accuracy (e.g. Stanislawski *et al.* 1996, Shi 1998)
Logical consistency (e.g. Lanter and Veregin, Huang *et al.* 1992)
Completeness (e.g. Tveite and Langaas 1999)
Temporal accuracy (e.g. Thapa and Bossler 1992)

While early work focused upon categorical error, later work by Hunter and Goodchild (1995) has been used as a base from which to assess the effect of quantitative uncertainties in elevation on slope and aspect (Hunter and Goodchild 1997) and through a landscape susceptibility model (Murillo and Hunter 1997). Others have drawn upon the kriging variance to simulate spatial attribute errors (e.g. Burrough *et al.* 1996) while increasingly the results of conditional simulation are presented for both categorical and attribute data (e.g. Mowrer 1997). It is this first step, defining the spatial component error present in a single GIS 'layer' rather than the exploration of the manner in which they combine and compound within a modelling scheme (Table 2-9), on which the GIScience literature has largely focused to date.

In many cases, the wide range of potential errors and difficulties in defining appropriate error functions for complex, multi-layer models means that overall global average statistics are still commonly used to assess error. Without either computationally feasible space-time error modelling tools or sufficient independent validation data, cross validation (sample re-use) techniques (Efron and Gong, 1983) are increasingly being used in a GIS framework to estimate error bounds (e.g. Mitásová *et al.* 1995, Willmott and Matsuura 1995). Drawing on accepted statistical theory, techniques such as cross-validation provide useful overall estimates of error, and provide point-based estimates of relative errors: Beard and Buttonfield's (1999) inclusion of them in their presentation of visual error analysis methods provides an indication of their acceptance within the GIS community as Table 2-10 illustrates. Additionally, as with independent test data the adequacy of any resample method is dependent on the adequate representation of the overall population characteristics within the data. Note also from Table 2-10 that error estimates over different point locations are not in general considered in the temporal dimension: the methodology developed within this study extends the current usage of cross-validation techniques within GIS.

Table 2-10. Error analysis methods and their corresponding dataset and context characteristics (After Beard and Buttenfield 1999)

Error analysis method	Data status	Applicable dimensions	Tasks	Computational complexity
Plots	Raw	X,y,z,a,t	Detection	Low
Consistency checks	Raw	X,y,z,a,t	Detection	Low
Ground truth checks	Processed	X,y,z,a	Detection, evaluation	Low
Adjustment computation	Raw	X,y,z	Detection, evaluation	Low-moderate
Cross validation	Processed	{x,y,z,a}	Evaluation	Moderate
Fuzzy classification	Processed	(x,y,z,a}	Evaluation	Moderate
Simulation	Processed	X,y,z,a,t	Detection, evaluation	high

The 'gridding' of the cross-validated error, which can be created using the sample interpolation techniques provides an enticing visual guide to the overall spatial pattern errors (Willmott and Matsuura 1995) and has been commonly encouraged over the past few years. However, such surfaces contain the limitations as the original sample despite Willmott and Matsuura's exhortation that '*Perhaps more importantly, spatial and temporal averages of the error fields obtained from a gridded rather than station-network field reduces the deleterious impacts of spatial sampling biases* *associated with irregularly spaced station networks*'. Additionally, if the spatial modelling is to any degree successful, there is little reason to suppose that the residuals are spatially correlated in the same way as the original data.

Discussion to this point has focused upon error within geographical data, rather than the biological models that will be using these data. Error propagation is used here to mean the propagation of error through conceptual models, rather than through simple rule based empirical models (termed here error *combination*). Since the biological models used in this study are process based, the expert systems approaches used previously to model error in pest hazard studies (Downing and Bartos 1991, Loh *et al.* 1991, Elmes *et al.* 1994) are not applicable in this case.

In the majority of studies, error is propagated through a limited set of data layers only: the approaches ignore the multi-temporal element so common within many environmental models (e.g. Phillips and Marks 1996, Magillo and Hunter 1997). As Figure 2-10 demonstrates, an ability to propagate error is reliant on the knowledge of error within intermediate data layers and preferably the model itself in addition. Rarely within either a GIScience or environmental modelling context however is the propagation of both types of error studied together, although there are notable exceptions (e.g. Davis and Keller 1997). Propagation techniques may themselves however be used to derive intermediate data layers, as Magillo and Hunter (1997) demonstrate, which may form part of a larger effort to track error propagation or contribute to an error combination approach.

As with the modelling of error within individual data layers, much of the earlier work on error propagation focused upon modelling categorical error (e.g. Goodchild *et al.* 1992, Lanter and Veregin 1992, Forier and Canters 1996) rather than the quantitative attribute data needed for agricultural applications such as this study. This is especially the case with regard to simple geographical models using buffering or overlay procedures. Work at Utrecht over the past 10 years (e.g. Heuvelink 1998, 1999) has been the primary exception to this situation. Existing statistical theory of error propagation using Taylor series, used for the propagation of errors over time in one dimension (e.g. Mowrer 1991, Gertner 1987) has been adapted to the spatial situation to provide fully spatial linked errors between logistic regression and kriging data models. The particular advantage of this work is that it allows for the assessment of individual contributions to the overall error score and contributes to error management and reduction strategies in addition to those lower in the error hierarchy (Figure 2-10). However, for more complex process models as in this study, such systems fail: as yet, they are unable to account for *space-time* sequences (Heuvelink 1998, p107). As Openshaw (1989) notes, under such circumstances, there is little option but to seek a more universal but computationally intensive Monte Carlo simulation approach. In principle, this Monte Carlo work is but a computational scaling up of the simpler *layer input data* type examples (e.g. Phillips and Marks 1996, Magillo and Hunter 1997). Henebry (1995) for instance uses Monte Carlo propagation to demonstrate within an ecological modelling framework the space-time sensitivity of a seed dispersal model to particular model parameters. Without high-performance computing equipment however, translating this theoretical possibility for error propagation into gridded sensitivities of insect phenologies is infeasible within this study. Moreover, the biological models used are deterministic rather than stochastic, such that the results would at best only represent partial uncertainties arising as a result of input data configuration only.

3 Methodological issues in assessing the geography of pest risk

3.0 Introduction

The principal aim of this study is to explore the space-time dynamics of insect phenology for non-indigenous and indigenous insect pest applications. As established within Chapter 1 (Section 1.6, p22), the primary modelling strategy used is the linking of spatial input data (daily maximum and minimum temperatures) with deductive process-based phenology models more commonly run at scattered point locations only. Consideration of the broad functional requirements is critical to the development of a methodology that will be 'fit for purpose'. Indeed, Hunter (1999) regards such a formalism of requirements as a contribution to reducing modelling uncertainties, and these are listed below.

Strategically, the methodology developed requires to:

- Provide a national (mainland England and Wales) perspective on insect phenologies both for indigenous species and particularly crucially, for pest risk assessment. The explicit use of a phenology model to assess pest risk assessment in unusual: more commonly used are *relative* indices of a pest's ability to develop, based upon a variety of empirical data.
- Cover a 30-year time span (1961-90) to allow inter-year variations in risk assessment to be explored. To date the majority modelling approaches to investigating establishment have been carried out using monthly 'climate normal' averages;
- Incorporate models for an indigenous (codling moth) and non-indigenous (Colorado beetle) pest and additionally a more generic accumulated temperature model that run on a daily time-step, in keeping with the short life span of many pests;
- Provide the spatially referenced input data (daily maximum and minimum temperatures) required by the phenological models, using techniques which minimise error owing to the known high sensitivity of insects to temperature;
- Establish strategies for integrating spatially referenced data and phenological models seamlessly;
- Model phenologies to a target resolution of $1km^2$. National geographical phenologies have not previously been computed at a national level, and temperature modelling over this extent and scale is unusual if not exceptional;
- Aim for modelling accuracies to be without prejudice to location. While non-indigenous pests are most commonly assessed as a threat to arable or horticultural crops, upland areas may also be at risk;
- Establish phenology-based measures that might assist the expert biologist in assessing the extent to which a non-indigenous pest has the capability to thrive on a year-on-year basis within this country;
- Allow the possibility of further, more specialist models of indigenous pests to be linked in the future, affording possibilities for system validation and day-to-day pest management opportunities;
- Achieve reasonably efficient computation, since national coverage for multiple years is required

which will involve significant volumes of data;

- Provide a means by which the error within the resultant phenologies in aggregate, and over time and space, may be assessed on a comparative basis.

In a similar fashion to Downs and Priestnall (1999), the objective in this overall approach was primarily to create a tool to meet the requirements for investigating the underlying research questions of the thesis. Efforts were made throughout the development of these tools to minimise data compromises and permit future multi-disciplinary integrative modelling, rather providing an immediate and user-friendly module for pest risk analysts. This is to support the thesis that the addition of the spatial dimension to PRA may lead to improved timing and more finely located risk assessments, at a nation-wide level.

The main elements of the geographical methodology for pest risk assessment suggested by functional requirements needed to explore the research goals (Section 1.5, p21) are illustrated within Figure 3-1. The chapter begins with a brief discussion of the specific phenology models used in the study (Section 3.1), introducing the structures and inputs and outputs required for the modelling of accumulated temperature, Colorado beetle and codling moth. Data considerations, both raw (Section 3.2.1) and manipulated by means of interpolation (Section 1), form the major element of this section of the thesis. The rationale for the selection of the particular meteorological and geographical data sets used in the study is explained, and the characteristics of the data are introduced. The interpolation methods used to manipulate these data are outlined in general terms. This discussion is then followed with more detailed coverage of the 'two phase' approach (multiple linear regression on topoclimatic variables + interpolation of the residuals) adopted for interpolating daily maximum and minimum temperatures.

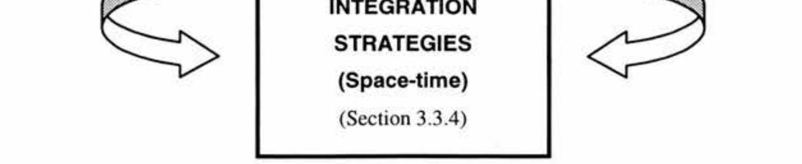

Figure 3-1. Major methodological units: organisation of chapter

The third important element in the methodology for exploring spatial phenologies is the means by which these elements are linked (Section 3.3.4). This section focuses on means of facilitating a flow of data from meteorological observation sites in a form that can be used to derive spatially-extended biological models. Several conceptual and practical issues are explained, for example that in insect ecology models have traditionally run on temporal sequences of point-based data and have historically lacked geographical reference, as are strategies for solving these.

The primary purpose of this chapter is to introduce the reader to the *primary* methodological concepts used within the study, for example the types of interpolation approach used and concepts of error propagation and assessment using cross-validation techniques. The following chapters will draw on knowledge gained regarding the nature of residuals, r.m.s. errors and issues such as complications arising when modelling phenological outputs in calendar dates. Specific experiments and detailed metrics associated with individual research questions (e.g. 'error metrics', Chapter 6), will be introduced on a chapter-by-chapter basis to allow the reader to juxtapose methods and results more easily.

3.1 Phenological models

The institutional link with CSL for this project was outlined within Section 1.4 (p20). Particular advantages of such a link include access to in-house entomological modelling expertise. Two phenology models have been selected by CSL as particularly appropriate for spatial treatment: a generic life cycle model (Baker 1985) based upon the well regarded PETE model (Welch *et al.* 1978) and a phenological/population model suite developed for Lepidopteran pests in particular at Horticultural Research Institute (Morgan 1992). These choices reflect the balance within the overall research motivation: to predict the long term risk posed by non-indigenous pests such as Colorado beetle, but without compromising the possibilities for the work to contribute to a management tool suitable for forecasting the development of native pests (e.g. codling moth). While developed under controlled conditions within laboratories, both models have been validated in the field by CSL staff. In order to provide an additional and more generic element to the task of pest risk assessment, an accumulated temperature model is also specified in the requirements. The details of these three models are found below in order to assist the reader in understanding the assumptions of these models and in interpreting model outputs. Their broad structural differences, following the discussion on temperature functions from chapter 2 (Section 2.1.2, p32), and for later reference within Chapter 6, are summarised within Figure 3-2 below.

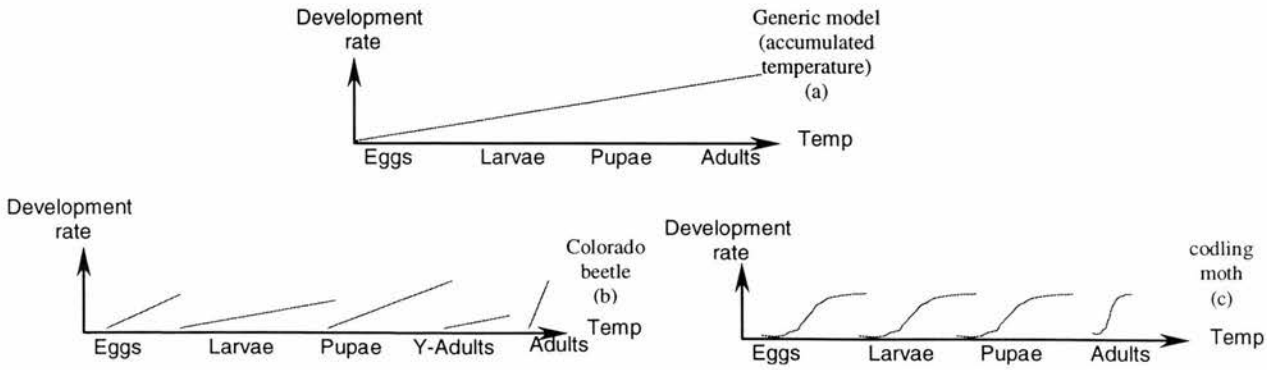

Figure 3-2. Three commonly applied approaches to modelling insect development rate over time

3.1.1 Accumulated temperature model

3.1.1.1 Model history

Heat accumulation units (or day-degrees) based on daily maximum and minimum air temperature observations are widely used within agriculture, and insect ecology is no exception as outlined within Section 2.1.2 (p32). A number of algorithms are used in order to account for the approximately sinusoidal diurnal pattern of ambient temperature, which integrate the area under the non-linear curve and above the lower threshold for development. McMaster and Wilhelm (1997) investigate the effects of these various methodologies for predicting corn development, and conclude that differences between algorithms can be significant. When expressing insect development as a function of accumulated temperature therefore, explicit specification of the underlying form of equation used to compute relevant thresholds is important, although these are not always clearly expressed. The day-degree functions used within this study are derived from the standard UKMO algorithm (Anon, 1969), which is based on the rectangular method of computation.

3.1.1.2 Model structure

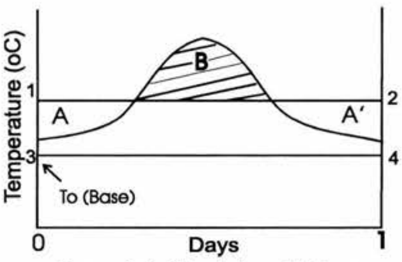

Figure 3-3. Calculation of daily accumulated temperatures (After Worner, 1992)

The UKMO method for computing accumulated temperature assumes that the diurnal curve is perfectly sinusoidal (Figure 3-3). Taking advantage of the symmetry of the curve, the line 1-2 cuts the temperature curve (max + min)/2 in half and so allows the area under the curve to be approximated by the rectangle 1,2,3,4. However, if the minimum temperature falls below the threshold (the curve falls below the line 1-2), this simplistic method will overestimate the degree day sum. The basic algorithm has therefore been adapted to that shown in Appendix 5.

3.1.1.3 Inputs to the accumulated temperature model

This model requires daily maximum and minimum temperatures, together with the specification of the chosen developmental threshold. DeGaetano and Knapp (1993) warn of the deleterious effect that differences in the time at which meteorological observations are made can have on accumulated temperature models, arising particularly in cross-border studies (e.g. Europe-wide). The standard 9a.m. UK Meteorological Office climate station recording time will be used in all cases in this study.

3.1.1.4 Model outputs

The univariate point output from the original UKMO algorithm is in accumulated degree-days (accumulated °C, also referred to as DD within the study).

3.1.2 PETE (Focus pest: Colorado Potato Beetle (*Leptinotarsa decemlineata*))

3.1.2.1 Model history

The original version of this deterministic model (the Pest Event Scheduling System, PETE), developed at the University of Michigan (e.g. Welch *et al.*1978), often forms a starting point for discussions on current computer based entomological modelling. Development of PETE was initially targeted at a deciduous fruit complex, towards organisms such as apple scab and codling moth among others (e.g. Welch *et al.*1978, Croft *et al.* 1980, Jorgensen *et al.* 1981). Today the modelling system still finds currency over a wide range of crops and pests (e.g. Harari *et al.* 1998). Baker and Cohen, working at CSL, extended its capabilities to include greater sophistication in its use of the primary inputs maximum and minimum temperatures. Additionally, field trials have been undertaken on the enhanced models within a British setting for native pests such as the wheat bulb fly (*Delia coarctata*) and codling moth (Baker, 1991). Tests of model accuracy for the non-native Colorado beetle in particular were carried out on the nearby Cotentin Peninsula as part of a European collaborative project (Baker and Cohen, 1985). It is on this latter work that this project draws in particular. The raw model code was made available for this project in FORTRAN 77.

3.1.2.2 Model structure

One single base temperature and an accumulated temperature sum drove insect development within the original form of PETE, like many other phenological models of its time. In contrast, Baker and Cohen's (1985) version of the program to be used in this study is adaptive between phases, incorporating development rates derived from temperature accumulations over base values set for each stage individually (Figure 3-4). As in the original model, within-stage development rates are also dependent on the shape of a Gaussian-like Erlang curve (Welch *et al.* 1978) for completion of the stage. A combination of linear rate temperature relationships (Figure 3-2, type b) are augmented by a sine wave calculation to model intra-daily fluctuations lead to a simple formula for calculating thermal time. Diapause is controlled using both an accumulated degree-day sum for obligatory change and by day length otherwise, reflecting photo-period induced change. Temperature thresholds for ecdysis (shedding of the old cuticle between developmental stages) have also been incorporated.

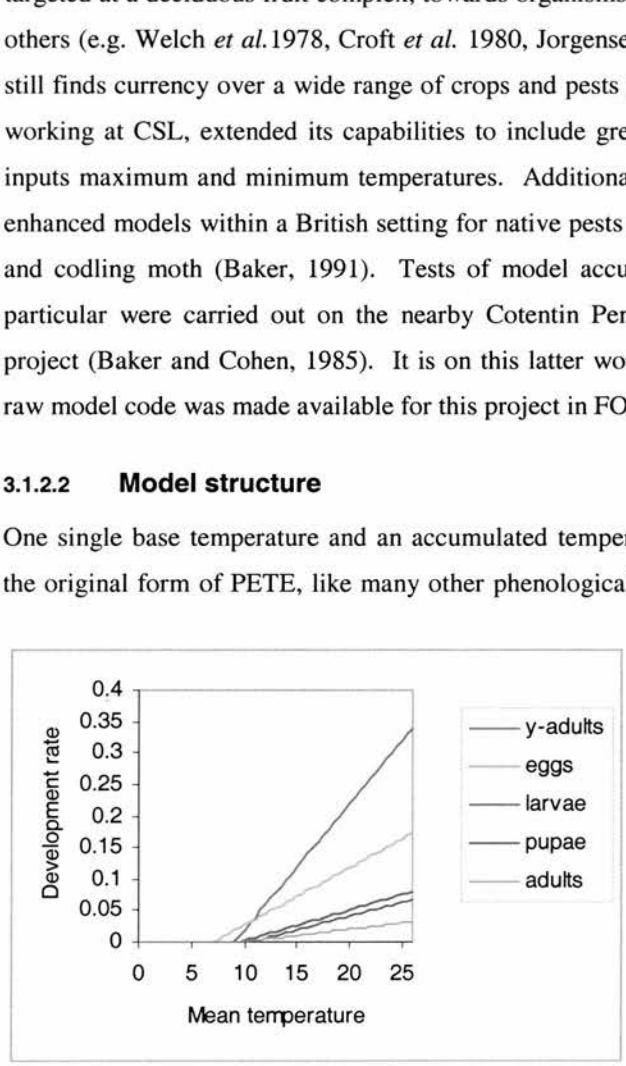

Figure 3-4. Development rates per Colorado beetle configuration file

The development of 100 notional individuals is simulated throughout discrete developmental stages, on the basis of degree-day time. By taking into account the variability in timing within one stage according to variant ambient temperatures using a time varying distributed delay model (TVDD, Manetsch, 1976), an individual need not necessarily pass through a complete stage unless the appropriate temperature accumulation and threshold for ecdysis is reached. No mortality is explicitly factored into the model and the overall population numbers are maintained in steady-state through regulation of the oviposition rate. The relative timings at which the individuals pass through the stages may subsequently be re-interpreted in phenological terms. This distinction between phenology and population was illustrated within Figure 2-5 (p33). The start and end of a pest development event and the peak activity (Figure 2-5(a)) may be inferred from the model, but not the absolute prediction in volume terms (Figure 2-5 (b))

Within the model structure, individual generations of a particular stage are not explicitly monitored. In the case of the test insect Colorado beetle, this presents little problem within the analyses presented for Great Britain. For other organisms, this blurring of generations may restrict the value of spatial model outputs for the pest risk analysis task since the number of potential generations provides an important element in assessing economic impacts. In an operational system therefore, program re-structuring would add to the value of the spatial information modelled: meanwhile, checks of tabulated outputs at a variety of locations serve.

3.1.2.3 Model input requirements

While Section 2.1.1 (p30) demonstrated the varied environment of the Colorado beetle throughout its life cycle, air measurements alone have been used to calibrate this model. The model requires maximum and minimum daily temperatures to run, although as a generic model it may be adapted to use measures of rainfall and solar radiation to dampen or enhance the pest activity level where those variables are particularly important. Soil temperature is less variable than air temperature, but nevertheless a bias towards the soil characteristics of Cotentin where the model was validated in the field is likely. Experiments with other soil based pests have shown that the substitution of mean air temperature for 10cm soil temperatures in the absence of an adequate soil temperature database may dampen potential population sizes achievable (Morgan and Jarvis, 1999). In this case, a lower threshold for larval development provides an implicit environmental compensation estimation for that soil based developmental phase. The models have been validated using standard Stevenson Screen temperatures from the nearest meteorological station. In order to incorporate photoperiod, day length is computed on the basis of latitude and Julian date.

In addition to the meteorological data requirements, the provision of a detailed biological parameter set is a critical element of this model. The structure of the model is generic to many pests, so this parameter file forms the means by which the biologist can verify and adjust the model for different surroundings without becoming entangled within the FORTRAN code. One such parameter file, that surroundings without becoming entangled within the FORTRAN code. One such parameter file, that used for the Colorado beetle explorations within the thesis, is illustrated within Appendix 6. In interpreting the results, it is important to note that for each initiation of the model, it is assumed that a standard number of adult pests, a notional 100, survived the winter and exist at a variety of ages within that biological stage. Diapause is broken as a result of increasing day length and temperatures. Given the wide variety in pests requiring to be assessed for quarantine purposes, the generic nature of PETE and the easily tailored parameter file is particularly significant.

3.1.2.4 Model outputs

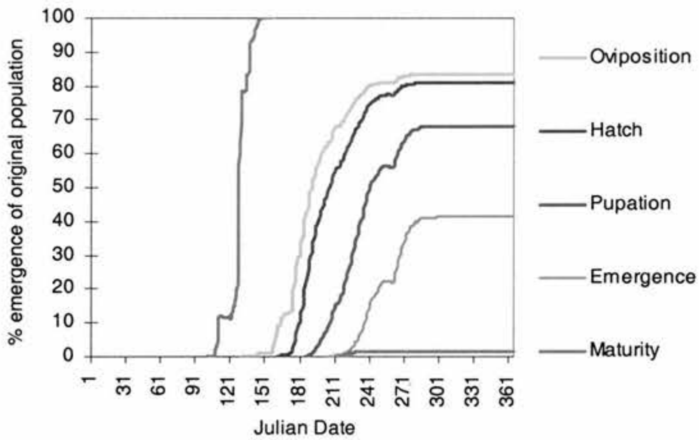

Figure 3-5. Example time series output from PETE for Colorado beetle at Bingley, Yorkshire (1976), converted to graphical form

Since the results provide an indication only of the timing of pest activity and not the size of the infestation (Figure 2-5), output data from phenology models are generally expressed as percentages. In this particular case, the standard program output provides an estimate of the cumulative proportion (0-100%) of the insect population that has moved to the next developmental stage. Because England and Wales lie at the margins for Colorado beetle development, the distributed delay function within the model (Welch *et al.* 1978) prevents a high proportion of insects in later stages of the lifecycle from moving through the developmental stages. Since only diapausing adults are likely to survive winter conditions, insect mortality for those trapped in other stages is implied. Cumulative percentage results for Bingley, Yorkshire for 1976 are plotted within Figure 3-5.

This model is used to exemplify the advantages of a geographical approach to pest risk assessment in Chapter 7. In support of the Julian date phenological results an 'activity index' (0-10) is computed within the model from which, after Baker and Cohen (1985), oviposition rates and flight capability may be estimated. High oviposition is associated with an activity level of 6 or over, while adult flight requires over 5 hours of sunshine on days of temperatures over 25°C: an activity index of 10 (Appendix 6). While the beetle is relatively static when close to an abundant food source, the measure of potential spread that this index affords provides supplementary information that may be important when assessing the ability to contain any possible outbreak.

3.1.3 PEST-MAN (Focus pest: codling moth (*Cydia pomonella*))

3.1.3.1 Model history

This deterministic model, developed at the Horticultural Research Institute and CSL (Morgan 1992, Morgan and Soloman 1993), simulates the phenology of the codling moth. Similarly to the PETE model discussed above, PEST-MAN has been developed using laboratory data and validated with trap data and temperatures estimated from a standard Meteorological Office station. Although the model may be adapted for other pests, it is not a generic framework in the same sense as PETE. PEST-MAN has been coded in FORTRAN 77.

3.1.3.2 Model structure

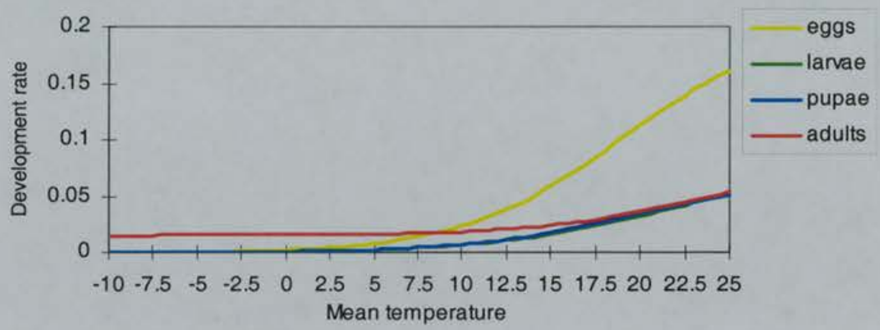

Figure 3-6. Development rates for codling moth, by stage

Both reproduction and development of the codling moth are dependent on both maximum and minimum screen temperature in a non-linear fashion (Figure 3-2, model type c)). In this model the development progress is controlled through specifying appropriate rates of development in each stage (Figure 3-6), rather than the use of thresholds to vary developmental progress as within PETE.

The form of non-linear relationship used is a logistic function of the form:

$$drate = a + \left(\frac{c}{1.0 + \exp(-b * (Tmean - m)} \right)$$

(Where *drate* is the development rate, and *Tmean* the mean daily temperature)

The progress of 100 individuals through their development stages is modelled in what is known as a BOXCAR routine (de Wit and Goudriaan 1978). Insects of the same physiological age remain together and are moved from one BOXCAR, or array element, to the next at each iteration. Survival is calculated hourly, according to the accumulated number of hour degrees. These temperatures are calculated within the pest model by fitting a sine curve through the maximum (2pm) and minimum temperatures for each day. Following the Carter *et al.* (1982) model for aphid development, updating of the BOXCAR population arrays starts with the oldest age class of the adult instar and works backwards to the youngest age class of the first instar. The model keeps track of individual generations, with the intention both of providing a better understanding of the population dynamics of the pest and also contributing to improved control strategies. In the case of codling moth, it is often a second, unexpected, generation that causes most economic damage to the crop. As such, this is an important feature distinguishing the practical value of this model over the field validated PETE parameters which exist for this codling moth in addition to the Colorado beetle already discussed. The incorporation of this non-linear model this provides an opportunity to investigate the relative sensitivities to model input error of the range of typical phenology models used in applied insect ecology.

3.1.3.3 Model inputs required by PEST-MAN

Daily maximum and minimum temperatures are required for this model. In order to incorporate photoperiod, day length is computed on the basis of latitude. The model assumes that a pest overwintered in pupal stage, and that diapause is broken as a result of increasing day length and temperatures. Alterations in development rate to compensate for alteration of major habitat within the life cycle (e.g. within/outside apple) are implicit within the field calibration that has been carried out in previous studies.

3.1.3.4 Model outputs

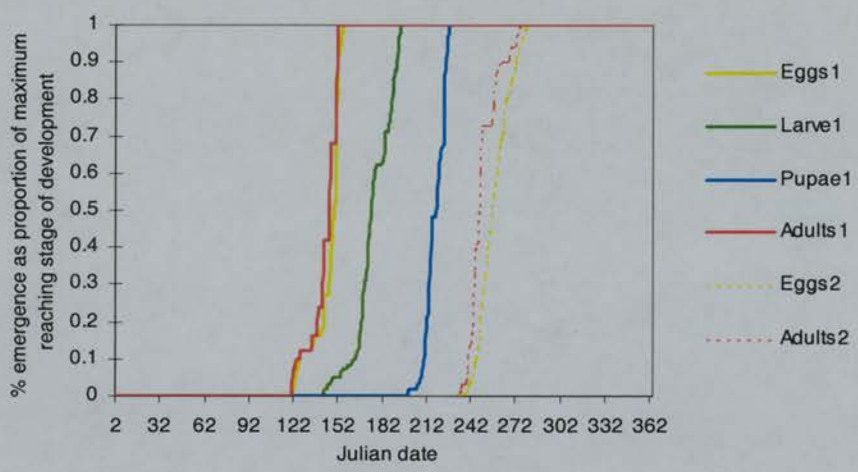

Figure 3-7. Codling moth development, East Malling, Kent (1990) computed using PESTMAN (Morgan 1992)

Since the results provide an indication only of the timing of pest activity and not the size of the infestation, outputs relating to pest development are generally expressed as percentages. An example of the model output is shown within Figure 3-7. In contrast to the accumulated development percentage outputs reported for Colorado beetle (Figure 3-5), progress through the life cycle is reported by a relative measure of the progress of the pest towards the date of peak activity within any one stage. Following the main cycle of the model, absolute numbers within each stage for each day are re-scaled through a second iteration as a proportion of the maximum reached. All first generation lifecycle curves will cover the full 0-100% range following re-scaling, where 100% is first reached at the date of the first 'peak event'. Initialisation begins with pupae at varying degrees of development. The need for daily rather than monthly input data is illustrated by the short span of the lifecycle of the Codling moth, like many other insects (Figure 3-7).

Critical periods in the pest control calendar are between 10% and 90% larval development when the pest is both accessible and physically vulnerable. Use of the maximum peak event to scale output percentages, rather than the cumulative percentage outputs of PETE, allows management events to be assessed relative to the timings for peak adults. These are relatively easily measurable using pheromone traps.

3.2 Data requirements

3.2.1 Meteorological data for phenological models

Models of pest development, as outlined within Section 2.1.2 (p32), rely predominantly on temperature inputs since temperature drives the major biological processes concerned. The specific non-indigenous and indigenous pest models to be used in the exploration of space-time phenological process, introduced above (Sections 3.1.1, 3.1.2 and 3.1.3), each rely on daily maximum and minimum air temperature data in particular as their major input variables. The derivation of daily maximum and minimum spatially referenced temperature sequences is therefore the logical starting point for this study.

Additional environmental factors such as soil temperature, solar radiation and precipitation could usefully be incorporated to influence processes as other biological research has shown (e.g. Weiss *et al.* 1993, Finch *et al.* 1996, Tauber *et al.* 1998). These variables are however more highly spatially correlated than daily maximum and minimum temperatures (Hubbard 1994) which, in association with their lower number of synoptic meteorological observation sites, makes their use more error prone. Soil temperatures for example are dependent on soil type, soil state and surface cover and cannot be taken from distant station observations with confidence (Wieringa 1997). More precise modelling requires calibration of soil temperature profiles with soil moisture and type, yet the British National Soil Series in digital form exists only at a scale of 1: 250,000. Such problems of representativeness are exacerbated when considering rainfall, which owing to its more variable distribution requires an extensive data set to model spatial autocorrelation adequately. While agricultural modelling has been carried out using rainfall figures interpolated from the British daily synoptic data set (e.g. Landau and Barnett 1996, Landau *et al.* 1998), exploratory variogram modelling in the context of this project showed a limited synoptic data set to be inadequate for the purpose. Similarly, while established trigonometric principles may be used to modify direct solar radiation (e.g. Dubayah and Rich 1995, Antonic 1998, Olseth and Skartveit 1997) the British recording network is sparse (approximately 50 stations). Standard UK Meteorological Office rules requires stations to be on level, exposed ground, making even an enhanced data set difficult to use in calibrating models for a full range of gradients and aspects. Furthermore, the fine mesoscale/toposcale grids (50-200m) suggested as most appropriate for modelling aspect-related microclimatic variations, particularly with regard to solar radiation and evaporation (Hutchinson and Gallant 1999) pose a considerable computer-processing problem when considering this nation-wide modelling scheme.

Given these complexities, the view taken for this study is that the underlying models have been validated in the field using air temperatures, and that these remain the principal driving forces behind insect development. Further biological modelling effort would be required to incorporate additional variables such as soil temperature and rainfall, which falls beyond the scope of this study. The sparseness of observation data for environmental modelling (e.g. soil temperatures) discussed above also hints at unreliable modelling accuracies for such input data. In order to focus upon the goal of integrating models and exploring spatio-temporal nature of the results, the provision of annual sequences of air temperature (daily maximum and minimum temperatures) to the phenological models therefore becomes the primary data requirement.

3.2.1.1 Sources of daily air temperature data

Climate data are a fundamental requirement for many environmental models, from those exploring forest fire and crop growth to hydrological processes. In many cases, especially for small scale or long term studies, monthly input data serve ecosystem models well. However, a number of models, especially those looking at short term environmental processes as in this case, require daily data and a range of options for deriving daily maximum and minimum air temperatures may therefore be found within the literature.

Deciding which option for obtaining daily air temperature data is 'best' for any one project requires a matching of temporal and spatial scales for the accurate representation of processes in addition to more pragmatic considerations of availability and cost. This scaling requirement is a function of both meteorological and biological process: as Steyaert (1993) and others have noted, identifying an appropriate scale for modelling is an important element within an environmental study.

Considerations of scale

Table 3-1. Scales in time and space, after Wieringa (1997)

Scale	Time scale	Horizontal scale	Vertical scale
Microscale	0.1 seconds to 1 minute	<1mm to 100mm	<1mm to 3m
Toposcale	3 seconds to 30 minutes	10m to 3km	1m to 100m
Mesoscale	1 minute to 3 hours	300m to 30km	10m to 1km
Synoptic scale	1 hour to 1 day	3 km to 1000km	100m to 10km
Macroscale	½ day to 1 week	30 km to 10^4km	1km to 20km
Globalscale	3 days and longer	300km to globe	1km to 100km

Qualitative definitions of scale in meteorology and climatology are widespread, such that similar terms may refer to a broad range of processes subject to author or even paper. Barrett (1979, p9) for example rather poetically characterises the mesoscale as the scale at *which '... relatively local embroideries upon a large, more generalised climatic picture are accommodated...'*. Specific quantitative definitions of scale are however preferable for consistency and one such classification (Table 3-1) provides a useful starting point for discussion. This particular schema (Wieringa, 1997) is used to stress the importance of the combined choice of spatial and temporal resolutions when modelling meteorological process.

The biological models have been parameterised using daily data from the synoptic network. Using the above framework, this temporal scale is associated with meteorological processes operating at scales between 3km to 1000km^2. Given the near ground environment of insects however, both toposcale and mesoscale scale factors all become important (e.g. Bolstad *et al.* 1996). Micro-climate is also important for pest development. Within codling moth life cycle for example, 'within apple' temperatures may be higher than those outside, leaf temperatures may differ on their upper and lower surfaces, and larvae may be more commonly be found on the south facing aspect of tree trunks (Blago and Baradinis, 1991). However, from orchard to orchard these differences might be assumed broadly similar in both space and time. The process by which the biological models have been tested and adjusted to field conditions following their genesis in the laboratory is therefore assumed to have generalised these effects when considering landscape wide, daily estimates. Moreover, insects are mobile and move not only between different microclimates at one location but between locations. Adult codling moths, for example, are known to roam for several kilometres (Schumacher *et al.*, 1997). Tying phenological development to a highly specific location for the entire span of the lifecycle of a pest may therefore provide a false sense of accuracy. Given the focus of phenological exploration rather than meteorological data per se in the thesis, 1km^2 is selected as the target resolution for modelling daily temperatures. Royer *et al.* (1989), considering the matter from the perspective of risk assessment from non-native pathogens, come to similar conclusions. A limited number of other studies (e.g. Landau and Barnett 1996, Van der Goot 1997) suggest that it may be technically feasible to produce estimates at this resolution using for example an interpolated approach.

3.2.1.2 Sources of daily gridded maximum and minimum temperatures at approximately 1km^2 resolution

The critical importance of temperature on ecological processes has ensured that spatial temperature data may be obtained by a variety of means, including:

a) Pre-gridded climatologies;
b) Satellite data;
c) Gridded results from general climate models;
d) Generation of data from climatic normals;
e) Interpolation of point meteorological data.

The most straightforward option, to use existing daily spatial data (pre-gridded climatologies), is not currently feasible as indicated within Table 3-2. In terms of temporal scale, the UKMO *MORECS* data at 40km^2 (Hough and Jones, 1997) is most suited to the task, but the daily data used to derive the product are aggregated to 10 day blocks. This product was developed in the 1980s and has seen little subsequent technical improvement. Additionally, the thirty-year span of data required for risk assessment is unavailable in this data series. Given the spatial scale of the pest environment, these data are considered inappropriate. No pre prepared data for Britain currently meets modelling requirements for pest risk assessment in both space and time domains, despite the potential use of such a data set for a variety of further agricultural and other modelling purposes.

Table 3-2. Pre-gridded temperature data for England and Wales

Sources of pre-calculated gridded data	Spatial scale	Temporal scale
Lennon and Turner (1995)	5*5km	Monthly mean temperatures
Tiger IV consortium (Barrow *et al.* 1993)	10*10km	Monthly mean maximum and minimum temperatures
UK Meteorological Office (1979)	5*5km	Seasonal accumulated temperatures
Hough and Jones (1997) [MORECS]	40*40km	Weekly maximum and minimum temperatures

Satellite data have been used to model *surface* temperatures, although the calibration required to convert these to maximum and minimum air values and problems with cloud cover (e.g. Kerdiles *et al.* 1996) combine with the short time span over which historical records are available to make this a less desirable option. In combination with other techniques, such as interpolation, however, the future holds promise. Petkov *et al.* (1996) for example improve their variogram modelling with NOAA-AVHRR thermal imagery. Other developments include the merging of numerical model results with ground temperature recordings to estimate air temperatures (Courault *et al.* 1998).

The most complex option, using outputs from process-based atmospheric models, is commonly used at monthly temporal scales or beyond. Although an interesting research subject, problems were anticipated in using such techniques for daily data at the 1km^2 scale required at a national level since most models operating at such grid resolutions relate to specific regions, are computationally intensive and require extensive land cover data. From a theoretical perspective however, pursuit of this type of methodology is preferable because it links directly with an understanding of meteorological processes. The work of atmospheric scientists such as Pielke, Avissar and Running for example (e.g. Avissar 1996, Pielke *et al.* 1993, Walker and Leone 1996, Running and Thorton 1996) who use detailed soil and land cover maps to parameterise their models, identifies the possibilities offered. Mesoscale numerical prediction models (e.g. RAMS, the Regional Atmospheric Modelling System) continue to improve (Cox *et al.* 1998). In this applied context however, given the nation-wide brief and multi-temporal nature of the linked pest modelling task, the computational complexity of such models were felt to outweigh the potential benefits of their use.

When assessing pest risk from non-native invaders the use of data simulated from a thirty year record ('weather-generated' data) is an attractive option. This approach is more often associated with crop modelling (e.g. Wallis and Griffiths 1997), especially when assessing the potential impacts of climate change (Semenov *et al.* 1996). Perhaps the best known generators validated successfully within a British context are WGEN (Richardson 1981) and LARS-WEG (Semenov *et al.* 1997, 1998), both available in the public domain. However, neither of these tools are spatially coherent. A random 'hot' day at one site might be partnered by a 'cold' day in another location of Britain within the same run, leading to an improbable spatial picture on a day-by-day basis since temperature is known to be spatially correlated rather than spatially random.

Table 3-3. Options for deriving full spatial estimates of daily maximum and minimum temperatures

Data source	Advantages	Disadvantages
Existing gridded data	• Allows more immediate focus on phenological modelling.	• Unavailable at spatial and temporal scale required (e.g. Meteorological Office 1989, Lennon and Turner 1995, Barrow *et al.* 1993); • No control or information regarding the quality of input data; • GIS unable to handle hundreds of daily surfaces required as input to an annual run of a phenological model.
Satellite data (e.g. NOAA AVHRR)	• Continuous gridded surface at 1.1km^2 compatible with modelling requirements; • Potential use in combination with meteorological data to better understand topo-climate; • Satellite derived ground surface temperatures reflect better the characteristic climate for larvae and pupae.	• Cloud coverage likely to render images incomplete; • Limited historical record and restricted range of variables; • Calibration requires knowledge of detailed land surface characteristics e.g. soil type, land cover; • Requires recalculations to estimate maximum and minimum temperatures (Cracknell and Xue, 1996); • Re-scaling problems; • Unable to incorporate climate change forecasts.
Gridded GCM model outputs	• Process driven and therefore theoretically advantageous; • Appropriate for variables such as rainfall where spatial auto-correlation is relatively local; • Can be used to explore changes in climate; • Stochastic simulation can be used to provide error estimates; • Technique extendible to other variables; • Potential forecasting capability.	• Requires understanding of atmospheric processes from local to global scales i.e. complex model; • Computer intensive to run; • 'Down scaling' still a current research issue to reach the required 1km^2 spatial scale.
Weather generated data	• Computationally compact; • Requires monthly rather than daily weather data.	• Full spatio-temporal generators are computationally complex; • Future use in hypothesis testing not possible (random).
Spatial interpolation of point meteorological data	• Can be computationally efficient, depending on methodology; • Well established theory and software; • Applicable to a variety of meteorological variables; • Relative parsimony of model owing to exploitation of spatial auto-correlation; • Ability to incorporate forecast data.	• Accuracy of interpolation weak where measured spatial auto-correlation is low; • Focus shifted from underlying processes; • As for GCM, stochastic simulation feasible theoretically but computationally intensive.

Only in aggregation over a monthly or longer-term basis, when individual sites tend towards the 'average' weather for the period, may results generated using simulated weather data be portrayed in spatial form. Work by Guenni (1997) and Hutchinson (1995a) shows the interpolation of intermediate model parameters to be a popular if simplistic form of spatio-temporal weather generation. Such a tool would be a useful addition to the pest risk assessment suite, both from the perspective of the long-term risk assessment of non-indigenous pests and for strategic planning in an indigenous pest setting. However, it would not assist with the development of a research framework for exploring the geographical elements of insect ecology where actual known relationships between temperature and pest behaviour must first be determined. Neither would the ability to simulate daily data assist with the development of real-time 'tactical' control and management strategies requiring validation using 'actual' data, although its value in narrowing down potential outcomes later within a year at the strategic level is acknowledged.

From the brief evaluation presented here and continued through Table 3-3, it is concluded that interpolating air temperature from ground weather stations provides the best possibility for representative spatio-temporal air temperature data for this research project. Critically, the long UKMO records with strong spatial coverage enable variations within the 30 year 'climate normal' period to be investigated and spatial autocorrelation to be modelled. They also afford the potential for modelling a wide range of further parameters such as relative humidity and rainfall, important for disease forecasts in the future. Additionally, interpolation procedures are well documented although at spatial scales of $1km^2$ and at a daily basis much regarding their effectiveness remains to be explored. Parsimony relative to more process-based approaches makes the interpolation approach a practical choice for applied work with large volumes of UK wide data. For these reasons, and given the disadvantages of the other approaches, interpolation was selected as method by which gridded daily temperature data sets for England and Wales were generated within this study.

3.2.1.3 Daily meteorological data set

The principal collator of long term weather data for England and Wales is the UK Meteorological Office. Within the past ten years alternative recording networks, such as road condition sensors, have also been established. Data from these latter sources are rarely used in conjunction with UKMO data owing to practical problems in merging network data given their potential differences of exposure, although exceptions are becoming more common (e.g. Brown and Murphy 1996, Jacobs and Raatz 1996). Cornford (1997) for example supplemented the UKMO network data with data from road temperature sensors in his work interpolating daily winter minima over Britain, although he found that these introduced considerable bias. While there would similarly be advantages in augmenting the basic UKMO data set for agricultural applications, sensors working to assist in road safety in particular do not record and transmit data during the summer months, when pest development is fastest. In order to focus this research effort and provide a base line over which further improvements may be compared, UKMO data alone were used.

UKMO data for the recording of daily maximum and minimum temperatures originate from two distinct station types: synoptic and climatic. At synoptic stations, automatic transmission of data is most common and the focus on quality control is most high: these are the data used to construct real time synoptic weather forecasts, the primary rationale behind the overall recording effort.

Augmenting this data set is further data collated, often manually and by volunteers, from climate recording stations. The locations of the UKMO climate and synoptic recording sites *consistently* open between period 1961-1990 is shown within Figure 3-8(a), which contrasts markedly with the full set of stations (Figure 3-8(b)) open at any time during the thirty-year period.

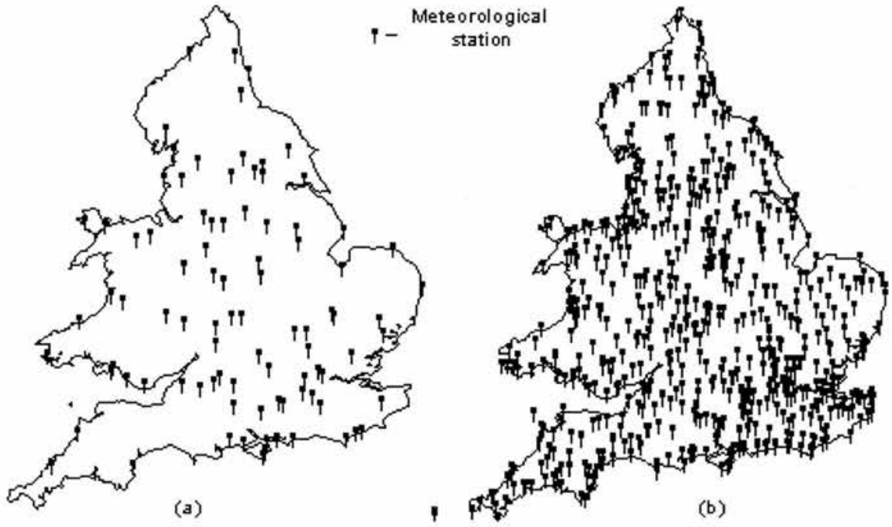

Figure 3-8. (a) Stations recording consistently between 1961 to 1990 inclusive and (b) Stations open for part of the period.

Selection of meteorological data

Since UKMO data are expensive to purchase, and a full set of daily synoptic data were not made available for use at the start of the project, the preliminary selection of an appropriate subset was necessary. Because of the variability in quality of data from meteorological office recording sites, it is necessary to undertake screening and selection of data. Criteria for selecting this subset include the need to ensure the data sample still retains representative environmental and geographical coverage, as well as the sites being distributed in a pattern that allows geostatistical analyses of the variation in observed parameters at sites of varying separation (Table 3-4).

Given the sensitivity of insect phenologies to temperature variation, the quality of the data is a foremost consideration since problems of missing or corrupt data must be identified and the records either infilled or rejected. In general, for reasons of speed of transmission and reliability, the synoptic record set is most commonly used in applied agricultural work. However, the UKMO network of stations has changed for a variety of reasons over time (Figure 3-8), one of the primary causes of which has been a more recent reduction in military land ownership. This means that, over the 30 year span modelled within this study, the locations of data used shift slightly throughout the period. Today however, the current UKMO philosophy is to minimise such changes (Hough, pers. comm.) and to focus strongly on reliable synoptic provision.

Table 3-4. Sampling criteria

A. Goal1: 'Representativeness' of sample data relative to full data set

- Adequate coverage of sites throughout country;
- Distribution of coastal/non coastal sites representative of those of UK as a whole;
- Distribution of heights representative of total range within UK.

B. Goal2: Sampling requirements related to interpolation tasks

- Nearby sites required for successful production of variogram;
- Long records required for improved temporal predictions;
- Currency of data important for management of future infestations;
- Where data recording has stopped but site important for other characteristics, time since recording discontinued.

As well as maximising length of record, a second important consideration was the degree to which the location of chosen meteorological stations reflected the underlying broad scale landscape features of England and Wales. Visual inspection of Figure 3-8(a) shows that the most consistent network has been located in lowland areas, with a marked bias towards coastal situations. In their representation of the overall landscape of Britain in terms of distance to the coast, height and terrain characteristics, the selected data are likely to be somewhat poor ('unrepresentative', Lees 1993, Aspinall and Lees 1994). If the pest risk assessment system is to be as generic as possible and bias with regard to the overall landscape minimised, sampling from the potential suite of stations needs to be systematic rather than random. Both upland and lowland areas need to be represented adequately, since a number of forest pests such as gypsy moth (*Lymantria dispar*) have the potential to cause considerable economic damage as the North American literature has shown (Table 2-4). Beyond purely economic issues, upland conservation and social issues may also need to be taken account by strategic policy makers when considering a pest risk assessment, adding to the argument for the results to be as fully geographically representative as possible.

The benefit of a stratified sampling approach that includes coverage of extreme sites is that the degree of extrapolation that must be carried out by the system is limited. This means that interpolated climate surfaces at the margins do not experience severe distortions and the predicted phenology values are therefore not grossly in error. Accounting for areas beyond those expected to be of agricultural value may however have a minor deleterious influence upon the results for the example pests of predominantly low lying crops (Colorado potato beetle and codling moth) modelled as part of this study.

A final consideration in selecting the locations of meteorological sites is that a degree of clustering of the data is warranted in order to improve the likelihood that adequate variograms may be computed: regular sampling schemes have been known to miss significant patterns of spatial autocorrelation. Too high a degree of clustering must also be avoided since this would require 'de-clustering' weights within the kriging analysis to be computed and would hamper the ability of partial thin plate spline techniques. Additionally, in order to avoid bias resulting from data clustered in urban areas, individual clusters should be spatially segregated. Urban areas are included within this pest risk modelling process since non-indigenous pests may potentially find refuge in urban gardens, which may be warmer than their rural surrounds and therefore prove particularly suitable for development.

A number of sampling methodologies may be found over a wide range of disciplines (e.g. gradsect sampling, Austin and Heyligers, 1989) which show an increased awareness of the need to maximise the possible environmental range within a sample. Other work within a geographical framework stresses the limitation of sampling within one dimension only (Lees 1994, Aspinall and Lees 1994). While theoretical advances have been made towards achieving both main sampling goals (representativeness of data and appropriateness for modelling) individually, in few cases are these combined. This is especially the case when considering selection from pre-existing data at fixed points: sampling practice remains 'ad hoc' under such conditions. Given that increasing volumes of pre-sampled point data now exist in electronic form, these omissions are an issue of currency within the wide range of topics embraced by the term 'environmental modelling'. That this increase in data richness has frequently been matched by the rising cost of data means the ability to select appropriate data is paramount not only in terms of model quality but also in the economic feasibility of the overall project itself. Applying the definition of Eastman *et al.* (1995) which classifies problems with a single objective (making an 'appropriate' sample choice) subject to a number of possibly conflicting criteria (representative data, multidimensionality, analytical requirements, cost) as multi-criteria evaluations, it can be argued that this sampling task is a multiple-criteria problem. A wide variety of traditional optimisation and search techniques exist which have been drawn upon in the development of 'multiple criteria decision making methods'. While a straightforward solution to the multi-criteria sampling problem was sought, a number of disadvantages in using these conventional methods were identified (search space size, the objective as a collective of suitable sites, and conflicting criteria selection), summarised within Appendix 2. Therefore, an 'ad-hoc' systematic sequential method was used which focused upon length of record, height and distance from the coast and thirdly geographical spread. A newer class of methods known as evolutionary algorithms (incl. genetic algorithms) that have been used in multi-criteria optimisation (Goldberg, 1989, p197) shows promise for this type of data selection task, and work in progress regarding the particular genetic algorithm structures and problem representation used is reported elsewhere (Jarvis and Stuart 1996, Appendix 13).

Sample characteristics

The selection criteria of Table 3-4 were used to add additional daily data for the years 1976 and 1986 to a preliminary daily data set for 1961-90 for 68 locations (Figure 3-9) initially made available to the project. The purpose of these extra data was to allow comparisons between more sophisticated interpolation techniques, and to better reflect the UKMO synoptic network. The new data set contained 174 points in total, adequate to allow the modelling of spatial autocorrelation within the temperature data using variograms. For the 30-year modelling required for pest risk assessment

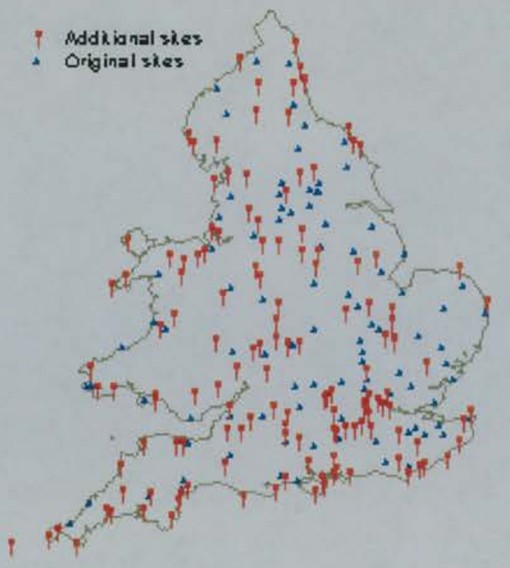

Figure 3-9. UKMO meteorological sites selected for use within the study (blue - original sites, red - augmented sites)

therefore, the volume of data available was variable. Although the principal benefits of the geographical phenologies constructed (which are explored within chapter 7) remain valid, the details of changes in pest risk from year to year should not be over-interpreted.

Bias within the original network makes true representativeness problematic. The location of the expanded network is shown in terms of elevation, distance to the coast and variability of height within Figure 3-10 for reference. Visual inspection of Figures 3-9 and Figure 3-10 suggests that the location of sample sites may be preferentially situated at the coastal margins. On average however, any 1km^2 cell in the overall landscape of England and Wales is only 31km from the sea while the sample data are on average 35km from the nearest coast. In the case of elevation, the average height for the complete landscape (at 1km^2 resolution) was computed to be 83m when using only the sample data and 125m overall, while the maximum elevations were 513m and 927m respectively (Figure 3-10(b)). Similarly, the standard deviations in elevations within a 50km^2 area around individual 1km^2 cells were 47m for the sample data and 60m across the landscape (Figure 3-10(c)). These statistics relative to those of the overall landscape suggest potential problems in constructing surfaces of phenology and temperature at high elevations, in complex terrain, and at the margins of upland areas.

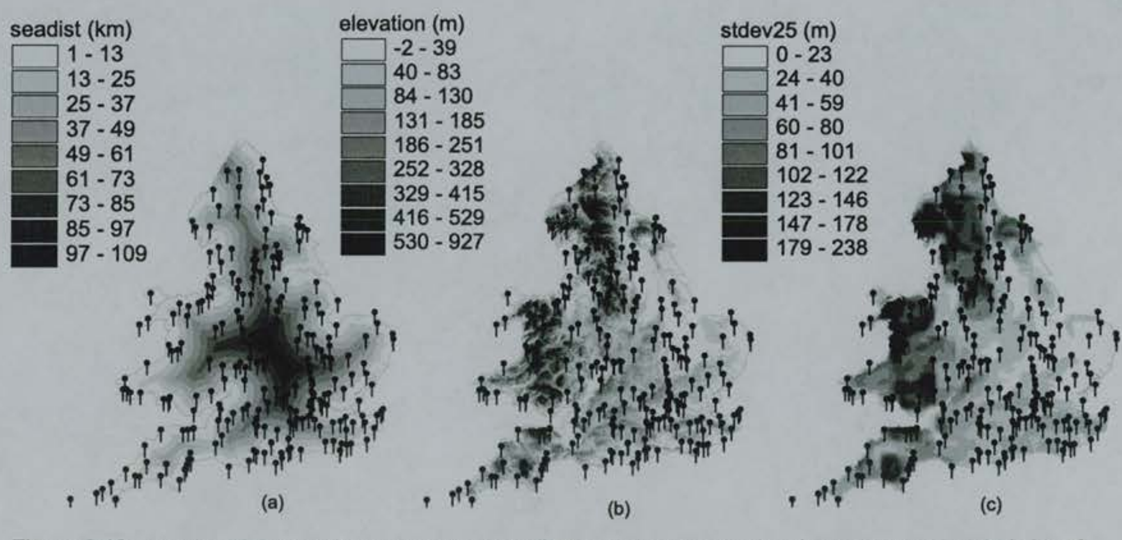

Figure 3-10. Location of selected sites with respect to (a) distance to the coast, (b) elevation and (c) standard deviation of height over 50km

Input data: quality assessment

The archived data obtained for the purposes of this study was provided under a quality assured agreement with the UK Meteorological Office. In the station selection procedure, '*Climaster*' meta-data describing the broad reliability of individual stations, both qualitatively and quantitatively, was supplemented by informal indications of reliability by experienced UKMO personnel (Baker, pers. comm.). As a result of such discussions for example, data from major airfields although necessarily of high consistency were omitted from the analysis.

Limited additional checks for internal consistency of the data sets were also carried out by plotting daily temperature series, revealing for example unvarying data from Dartmoor prison. Heights provided by UKMO were compared with those obtained from 50m digital Ordnance Survey elevation data, revealing anomalies such as roof-top urban stations of non-standard exposure, such as for example the Post Office Tower in London. Within the post-processing of inconsistently formatted UKMO data files, the date sequences for data were also checked and data outside the range of –20 to 35°C were excluded from further use.

The literature on handling missing meteorological data suggests a variety of approaches to this recurring problem, especially within the climatic as opposed to synoptic records. Within a British context, Parker (1998) of the UK Meteorological Office suggests estimating missing daily data from hourly records: however, the latter are often not available from climate stations and as such have not been collated for this study. Failing this possibility, Parker suggests that the 'nearest neighbour' data be substituted. Contrasting this simplistic approach is that of Glasbey (1995), who in the context of solar radiation investigated the relative benefits of temporal and spatial averaging when substituting for missing data. Such results will depend critically on the relative strengths of spatial and temporal autocorrelation however: in an extended network as in this study, the spatial variability of the recording network is likely to render any findings non-stationary. Within this study, missing data for one day only is substituted by an average of the previous and next day's records, to a maximum of 20 substitutions per year. Sequences that fail this criterion were omitted from analysis.

3.2.2 Meteorological data for validation of climatic surfaces

Carrying out an independent 'benchmarking' of a model is an important component within any scientific methodology, although an area in which the literature regarding interpolated temperatures is not always consistently strong. Two main options are possible for validating the individual interpolated surfaces:

1. Validate results against a completely independent data set;
2. Assess using re-sampling techniques, such as bootstrap or jack-knife cross-validation (Cressie 1991).

For scientific rigour, the use of an independent data set for validation is the preferred option. Validating the performance of an interpolator on the data used for modelling will not necessarily be a good estimate for unseen data because the model may have been over fitted: non-typical or outlying data within the sample may have assumed disproportional importance. The system then lacks the ability to generalise as a result.

Just as for the original data used in modelling, the validation data set should also be representative of the population being sampled. In cases where the only (often financially imposed) option is to divide the original data set, where data at the extremes are already limited, this may cause compromise both in terms of the modelling ability and the test statistics. Means by which data could be partitioned without compromising the modelling phase required consideration. With an efficient limited original sample, as is the case for this study, the volume of data is likely to be insufficient for this to work. Indeed, Lees (1993) categorically states that splitting a data set in half and hoping that it will be representative is an inadequate approach. Where the volume of data allows it, the literature suggests that two mutually exclusive sample sets be built in parallel rather than one set be chosen and subsequently split. For computational efficiency, only almost complete temperature records were used within this study (Section 3.2.1, p87). Data from sites only open for part of the year would therefore qualify as independent, and have been used to assess other studies (e.g. Rigol 1998). However, such data are also likely to be from remote or amateur climate stations: either unrepresentative or potentially of doubtful consistency. They are also not necessarily at consistent locations over time, reducing the interpretability of temporal variations in error. For these multiple reasons, the jack-knife cross-validation method attributed to Tukey was chosen as the primary means of model verification within this study.

Jack-knife cross-validation refers to the practice, for each sample point in turn, of iteratively omitting the point from analysis (in this case, interpolation), computing its estimated value and re-inserting it. The estimated values together form an approximation to the overall error distribution (Cressie, 1991). Cressie (1991, p489) observes regarding these methods *that 'techniques for estimating a statistic/estimator's distributional properties have proved their worth in situations where very little can be assumed about the underlying distribution of the data'*, although they are better suited to data without geographical dependencies. Fu (1994, p331) makes the useful distinction that cross-validation *verifies (examines for this purpose:* OED) the model while further independent testing *validates (ratifies, confirms, makes valid:* OED*)* the performance of the resultant 'best' model. In other words, the role of cross-validation is primarily to highlight potentially troublesome prediction points. It cannot prove that the fitted

Figure 3-11. Location of additional fully independent validation data, 1976

model is correct, merely that it is not grossly incorrect. This algorithm for this jack-knife cross-validation method is further explained in Section 3.3.3 (p117).

At a late stage in the project, a full climate and synoptic data set for the year 1976 was made available, allowing a fully independent validation over an additional 100 site locations. The locations of these data are shown within Figure 3-11. These data were used to assess the validity of the cross-validation approach in estimating the accuracy of daily maximum and minimum temperature interpolations for the 'best' performing interpolator and also for the results from the accumulated temperature model (Chapter 5).

3.2.3 Topographic/geographical data

As highlighted within Section 2.3.2, the use of variables to guide interpolation where data sets are sparse has the potential to improve modelling considerably. Given the known strength of dependence of temperature on elevation, digital height data are particularly important within this study. In common with many other environmental modelling and natural resource assessment studies (Band 1999), a regular grid DEM is preferred for the task in order to tie in with the raster output approach of common interpolation algorithms.

The principal raster data used within the study was the Ordnance Survey Panorama product, at 50m resolution, for England and Wales. This data set was derived by the Ordnance Survey (OS) from the digitised contours of the 1:50,000 *Landranger* map series, and is gridded to a vertical precision of 1m with spatially averaged error estimates to within $\pm$5m (OS 1996). These raw data were used to derive an approximate drainage network using the default hydrological commands within ARC-INFO, following which all further processing was carried out using 500m^2 or 1km^2 grids constructed using standard GRASS re-sampling procedures. Hutchinson and Gallant (1999) concur that '*Mesoscale DEMs, with spatial resolutions from 200m to 5km, are appropriate for topographically dependent representations of surface temperature and rainfall, key determinants of biological activity*' and that '*this scale is also useful for ... providing fundamental terrain and climatic constraints on agricultural productivity.*' Work by Monckton (1994) among others has investigated accuracies of these specific data and found no systematic spatial arrangement of errors beyond distances of 250m and the mean vertical error to be within 1m – albeit with a slight negative bias. For the purposes of this study the data were taken as correct: noted problems with East Anglian drainage systems in earlier versions of the product have now been corrected (Parks, pers. comm.). The adequacy of this approach relies, in addition to Monkton's assessment, on the assumption that for this study absolute elevation (and lapse rate effects) is more important than a detailed representation of land surface shape.

In order to begin to accommodate known alterations of temperature that arise as a result of urbanisation effects in addition to those of topoclimate, the elevation data were supplemented by 'urban' and 'suburban' class data from the Landsat-derived ITE landcover data set (Fuller *at al.*,

1994) available at $25m^2$ resolution. The 'urban' class incorporates all urban developments to the exclusion of significant quantities of permanent vegetation, while the 'suburban' category includes mixed built/vegetative land covers and small villages or rural industrial estates. These data were used to develop crude measures of urban effects through a derived urban index (p97). Issues of temporal consistency relating to this use of a single static measure for modelling over a 30 year period are acknowledged.

The final geographical data set used in this study was a digital coverage of areas known to be growing agricultural crops, in particular satellite derived land use data from Edinburgh Data Library indicating areas under potatoes in 1994 ($ha/2km^2$). The rationale for including crop cover data was to allow national estimates of the risk of an agricultural crop pest's distribution through the year to be related to the availability of a co-incident food supply. In many cases, the absence of a host crop (through harvesting or its unsuitability to particular locations) may be a major constraint reducing the ability of a pest to survive in certain areas even in cases where temperatures are not limiting. Because the computerised data themselves have a number of limitations, and the year to year distribution of areas planted is known to be quite variable, care is needed in suggesting that a crop distribution from one particular year can be used to limit risk mapping. Nevertheless, it was thought valuable to include these data in the later stages of the results, to indicate the potential for finely tuning risk assessments according to crop (food supply) in addition to temperature conditions.

The sources of data used in the project, both geographical and meteorological, are summarised within Appendix 1.

3.3 Development of a system for the interpolation of climate data and the spatial estimation of insect phenologies

At the beginning of this chapter, the design of a prototype system to explore insect phenology in space-time was firmly focused on meeting the functional requirements required for geographical analyses. Parks (1993, p33) suggested that: '*Whether such functions are to be supported entirely within or outside GIS software is less important than the engineering of workable linkages…*'. While significant research issues remain if the many theoretical developments in space-time modelling are to be incorporated into proprietary GIS (Peuquet 1999), these do not form the goals of this applied study. Rather, a pragmatic stance is adopted in order to retain a focus on the primary aim. Parks (op cit.) continues with the observation that '*… models whose value is not strictly limited to the research sphere or that are already widely accepted are often not easily implemented by the variety of users that might benefit from them.*' The interpolation routines and error propagation functions required within this project provide prime examples of procedures that need to be made more accessible and integrated so that they can be selected, compared and implemented within a broader range of applied studies.

3.3.1 Hardware/software configuration

Typical options for implementing a system to support applied GIScience research are presented within Table 3-5. These relate to the underlying hardware or software configuration required, in particular to the spatial analysis functions afforded by stand-alone software and proprietary systems versus those available in public domain research code. The possibilities afforded for developing 'workable linkages' between process models and GIS environments (operability) are also noted.

The speed of development on computer technologies (Moore's Law, for example, suggests that computer processing speed will double every 18 months) means that anachronisms will inevitably arise in the development of GIS implementations. At the initiation of this study a UNIX platform offered the greatest computational opportunities both in terms of available memory and processing speed: the national remit of the study together with the known computational intensity of kriging and partial thin plate splines interpolation methodologies confirmed its selection. Today, however, the GI applications scientist more typically uses the Windows environment (Elshaw Thrall and Thrall 1999) for its ease of software interface development and user interaction. . Given the mathematical nature of the methodologies being investigated, there is still strong rationale for the use of UNIX systems for a project such as this. For example, the incorporation of mathematical matrix libraries as standard by major UNIX vendors in their software development toolkits while their continuing support and improvement of FORTRAN compilers (the language in which much public domain mathematical code is still written) is strong. As Table 3-5 identifies, this choice of UNIX platform was not a constraining one.

Table 3-5. Software options for linking pest models with geographical inputs - creating a system to facilitate analyses

System	Sophisticated interpolation techniques	Computational efficiency	Link to low level code for point process models	Ability to handle data in temporal in addition to spatial sequence	UNIX based	Ease of 'reasonable' cartographic display	Error propagation facility	Interface development facilitated
ARC-INFO	X	X	✓	X	✓	✓	X	✓
GRASS	✓ (but integer based, X)	✓	With programming	✓	✓	X	X	X
RESEARCH SOFTWARE e.g. Anusplin, GSLIB	✓	✓	✓	With programming	✓ Platform independent	X (Reliance on established GIS product)	✓	X
SURFER	✓	✓	X	X	X	✓	X	X

3.3.2 Strategies for interpolation

The literature review highlighted a number of research issues relating to the interpolation of temperature as a component within an applied modelling framework. Much remains to be explored using techniques such as partial thin plate splines or ordinary kriging in an applied context for interpolating at a daily time step. These families of methods are relatively rarely discussed either singly or in comparison at this temporal scale and using automatic calibration of critical model parameters. As an integral component within agricultural applications, yesterday's standard methods such as trend surface analysis and inverse distance weighting remain dominant.

The work reviewed suggests a role for:

- Increased consideration of topoclimatic parameters to guide interpolations (e.g. Bolstad *et al.* 1998, Landau *and* Barnett 1996) at a daily time step. Lennon and Turner (1995) and Cornford (1997) present research based on monthly maximum and minimum data at $5km^2$ resolution and daily winter minima at $500m^2$ respectively for Great Britain. The importance of including further topographic factors within analyses of daily maxima and summer minima are highlighted but remain unexplored.
- A more consistent approach to comparison between interpolation techniques for interpolating daily temperatures, specifically the avoidance of bias owing to the use of different guiding variables to assist the interpolations practised by others (e.g. Collins *and* Bolstad 1996, Bolstad *et al.* 1998) and use of a data set of sufficient volume such that no particular method (e.g. kriging) is theoretically disadvantaged *apriori* (e.g. Nalder and Wein, 1998).
- The exploration of partial thin plate spline performance in comparison to kriging in this applied context. Will partial thin plate splines 'over-smooth' daily temperatures, or will their automatic parameter setting facility confer greater advantage in absolute error terms? Table 2-6 illustrated that the number of such comparative analyses using daily maximum and minimum temperatures remain sparse.
- Comparisons between simple and more complex interpolation techniques to address the question whether choice of interpolation method is subservient to the effect of introducing more advanced topographic modelling of guiding variables. This has been hypothesised by others (e.g. Cornford 1997) but remains untested (Table 2-6 and Table 2-7 in conjunction illustrated this gap).
- Greater rigour in error analyses, for example by using r.m.s. error in preference (or addition) to correlation coefficients (e.g. Landau *and* Barnett 1996), greater number of days used to generate accuracy results in view of hypothesised seasonal and day-to-day variations in error (e.g. Collins *and* Bolstad (1996) consider a 10 day average), and use of semi-independent (jack-knifed) and fully-independent data to verify results (e.g. Landau *and* Barnett (1996) provide non-independent results).

The remainder of this section on interpolation strategies is structured as follows. The process of estimating daily temperatures at gridded locations throughout the landscape of England and Wales has been shown from the literature to be improved in most cases by the careful selection of 'guiding' topo-climatic variables. Firstly therefore, methods are presented for deriving topoclimatic variables at continuous positions over the landscape of England and Wales, using mainly GIS techniques. A method is proposed of selecting a subset of the more influential topo-climatic factors to guide the interpolation of daily maximum and minimum air temperatures. Secondly, differences in the estimation of gridded values are also influenced by the sophistication of the method of interpolation that is subsequently used, specifically how flexibly guiding variables and other information on local dependency can be incorporated in the estimation process. The method of interpolation to be used for the generation of daily temperature grids in the remainder of the thesis (Chapter 5 onwards) will be selected from a number of candidate methods. The criteria for selecting the 'best' technique will be outlined.

The results of both analytical steps will be presented as Chapter 4. The process of selecting appropriate guiding covariates was carried out using data from 1986, while the accuracy of the interpolation results using the selected variables will be assessed in Chapter 4 using data from 1976 in order to maintain temporal independence.

3.3.2.1 Deriving topo-climatic variables to guide the interpolation of temperature

When selecting variables to guide interpolation, the first step is to consider the underlying processes affecting daily maximum and minimum temperatures. The approach followed has many similarities to the methods of Cornford (1997) and echoes older British topo-climatic research. (e.g. Tabony 1985, Manley 1944). The methodology of Lennon and Turner (1995), although devised for monthly data, has also guided the approach taken. As outlined within Section 2.3.3 (p61), this literature points to the importance of the distance to the sea, elevation, latitude and the degree of urban development as primary variables to guide the interpolation of temperatures in a British context. For consistency, the methodology outlined in this section follows the surface type/topography headings of Table 2-8 above. This methodology differs in aim from Cornford (1997) in that full parameterisation of the physical situation (albeit in empirical terms) is not the underlying goal. The rationale is rather to explore the pragmatic hypothesis that the inherent capabilities of an interpolation method and the presence of spatial autocorrelation in air temperature data over England and Wales are likely to compensate for a certain lack of detail in topo-climatic conditions. This assumes that the main guiding variables that operate across the country may be measured continuously.

On the basis of the existing literature describing the interpolation of daily air temperature for Great Britain in particular (Cornford 1998, Lennon and Turner 1995 and augmented by Tabony 1985 and Manley, 1944) 35 variables (Appendix 7) were selected for consideration. Fewer variables were considered in this study relative to Cornford's owing to the expected compensatory effect of spatial autocorrelation discussed in the previous paragraph, the applied nature of the project and the information learned from the prior studies. All topo-climatic variables were computed to a grid resolution of $1km^2$.

Surface type

Net radiation absorbed

Incident radiation is partly reflected and absorbed. The immediately reflected portion defines a surface's 'albedo'. Land surfaces for example heat and cool more quickly and have greater temperature ranges than water surfaces. Minimum temperatures in particular are more highly affected by albedo since at night the location and vegetation dependent soil heat flux is a relatively large part of the energy balance (Wieringa, 1997). These microscale terrain influences are not easily resolved without current digital land cover and soil mapping. Additionally, quantifying 'average albedo' varies according to study (Linacre, 1992, p92) and within standard texts (e.g. Barry and Chorley, 1982). Use of the ITE landcover data set provides one means of gridding countrywide albedo as demonstrated by Cornford (1997), although issues of temporal change arise given the static nature of this product. Its incorporation into the UKMO mesoscale model (Jones 1996), running at approximately $10km^2$ grid resolution, proved to be inconclusive in helping to estimate daily temperatures although was found to moderate wind speed significantly. This result may however be scale dependent, especially given the level of fragmentation of British land cover. However, neither these ITE landcover data nor soil data of adequate resolution (the national digital coverage stands at 1:250,000) were available for this study.

Internal boundary layers

Relative differences in latent heat flux set up temperature and wind gradients, giving rise to temperature gradients for example at forest edges. Local, highly detailed studies of those such as Blennow and Perrson (1998) and Lindkvist and Lindqvist (1998) for example focused on temperature effects within and outside forest canopies. However, given the local scale of many of these effects and restrictions imposed by lack of land cover mapping in this study, such microclimatic influences are not considered further here. Sea breezes are discussed below as a component of topographical discussion. Within empirical studies such as Blennow and Perrson (1998), attributing the temperature changes encountered between the effects of latent heat flux and surface roughness inevitably becomes blurred.

Surface roughness

Exposure to winds can affect daily temperature range at the toposcale (p79) by altering the surface wind speed: stronger winds are associated with a reduced range in temperature. A reduction of horizontal wind speed in forest clearings increases the hazard of frost, for example. A wide range of empirical measures have been used within the literature to account for surface roughness. Modelling at $500m^2$ resolution, the standard deviation of elevation within a $500m^2$ grid cell has been investigated as an explanatory factor of daily winter temperature minima, but was not found to provide significant explanation (Cornford 1997). Echoing Tabony's (1985) measure of local shelter, further measures of local roughness developed by Cornford (height – mean height for 25km and height – mean height over 5km radii) proved of greater worth. However, these indices do not necessarily mimic the shape of the underlying land surface and wind flow and a 25km radius could for example straddle two drainage basins. Lennon and Turner (1995), similarly looking to reflect surface roughness, include minimum, maximum and mean elevation values over both a $5km^2$ square and a $45km^2$ area as independent regression terms when modelling monthly temperatures in addition to the elevation of the local cell where the temperature is to be estimated. Their results point to the retention of the more local factor, but not that at $45km^2$, suggesting that Cornford's 25km radius best captures the effect of variation in elevation on temperature. Factors incorporated within this work reflect both local shelter and broader scales of air flow, using the 5km and 25km radii in recognition that daily temperatures are likely to be more locally variant than monthly averages. For these reasons, the standard deviation of height within local rectangular windows of 5km and 25km width were computed (stdev5 and stdev25, Figure 3-12(h)). In addition local surface roughness as 'height above the local average elevation' was derived by subtracting the target cell height from the average elevation found over similar rectangular areas (rough5, rough25, Figure 3-12(g)).

Urban effects

The significance of urban areas on interpolated temperatures for Britain is illustrated by Lennon and Turner's (1995) observation that when estimating monthly maximum and minimum temperatures '*Nearly all the large positive values (residuals), and some of the weaker ones, are centred on urban areas.*' Landau and Barnett (1996) also found their omission of this factor was highly significant in explaining the location of their residuals for minimum temperatures. Heat emissions, changes in albedo, and pollution are among the causes of the 'heat island' effect that is reported to have a particularly strong effect on minimum, rather than maximum, temperatures. In one of the rare studies that incorporates this effect into the interpolation process, Cornford (1997) constructed gridded variables indicating distance to the nearest urban feature and secondly the percentage of urban cover within a number of local radii to a maximum of 5km. However, the literature on heat islands suggests two reasons why both such indices are lacking. Several studies indicate that the urban effect declines steeply at the edge of suburban areas (e.g. Oke 1976). Additionally, the measures proposed ignore the findings that the heat effect is linearly related to the log of the size of urban population (Oke 1973), and the fact that many of Britain's conglomerations exceed a radius of 5km. An alternative index was therefore modelled using ITE land cover of urban and suburban areas.

Cells classified as 'urban' or with greater than 20% 'suburban' land cover were amalgamated to from a binary (1/0) urban grid, which was aggregated to a 2km resolution grid. This generalised binary grid was converted to a polygon coverage representing cohesive urban areas. The area of each polygon classified as 'urban' provided a measure of the size of conurbation within which any cell tagged as 'urban' was located. Individual cells were assigned a value represented by the natural log of the urban area within which they were located. These log values were then multiplied by the original percentage measure of urban/suburbanisation of the $1km^2$ grid cells. This gridded 'urban index' therefore provided a measure both of urban density as a function of the overall size of the settlement of which any particular cell belonged (urban, Figure 3-12(a)).

Topography

Lapse rates

The attenuation of air temperature with height is known as the adiabatic lapse rate, and is approximately linear with height until the troposphere is reached (Lamb 1972, p9). At higher altitudes, there is a greater net loss of terrestrial radiation because the lower density of the overlying air results in a smaller fraction of the outgoing radiation being re-absorbed. The 'standard' British rate is given as $-0.6^{o}C/100m$, but as Manley (1970) notes this may alter between seasons between $-0.7^{o}C$ in April/May to $-0.6^{o}C$ in November subject to the density of the overlying air mass. However, use of a seasonally or even monthly invariant lapse rate cannot account for inversions or other local atmospheric irregularities. Manley (1970) for example suggests that 'rates in the south of England are steeper than in the north of Scotland, though this may be due to more sheltered climate stations in the North'. Additionally, longer winter nights may increase the intensity of the inversions when they occur. Exposure also affects lapse rate through modification of the available water budget (Linacre 1992, p73). The use of static lapse rates to predict maximum temperatures is more reliable than that for minima. However, as Bolstad *et al.* (1998) have shown, even lapse rates that are defined locally and by season are no substitute for more adaptive (adjusted daily) techniques unless a wider range of parameters are also included. Within this study, regression equations were computed on a daily basis to ensure maximum flexibility with environmental conditions.

Variation in solar radiation received

Wieringa (1997) suggests differences in radiation intensity on sloping surfaces qualify as toposcale (10m to 3km) effects. However, Tabony (1985) suggests that above a resolution of 0.5km the topographic data set is too coarse for the effects of slope and aspect to be considered. Cornford's (1997) results support this claim, although Lennon and Turner found large scale slope to the south (but not west) significant on a $5km^2$ resolution grid. Since slope and aspect are known to affect insect behaviour at a local scale (e.g. Weiss *et al.* 1993), a number of variables were constructed. Aspect is expected to exert a greater influence on maximum, rather than minimum, temperature although it is possible that shading in winter may considerably reduce the diurnal range in some valleys. A simple index (aspect) was developed to reflect this possibility using Arc-Info's *ASPECT* facility, where 1 represents a south facing slope and –1 a slope with north facing aspect. Questions of screening and shading were not addressed as these mostly influence solar radiation received rather than temperature. The influence of solar radiation will affect pest development primarily through the alteration of photoperiod.

Cold air drainage and evaporation on slopes

Surface cooling by latent heat transfer occurs where there is evaporation. Thus the heat capacity of soil alters subject to its wetness. The notion that damp soils are more likely at valley bottoms was encapsulated by representing distance to the nearest rivers of various 'Strahler' orders (in which the labelling of a stream reach does not change until a stream of equal or higher order is joined to it). In the absence of a digital data set, the 50m elevation data was used in conjunction with the standard recommended ARC-INFO (GRID) commands to model a hypothetical drainage network (ESRI 1991), having first eliminated any spurious 'sinks' within the raw data. Band (1999) discusses a variety of recursive global sequential operators typically used for this process: the algorithms of Jenson and Domingue (1988) are those used within this software. Subsequently, the derived flow grid was aggregated to $1km^2$ resolution and each landscape cell was assigned the distance to its nearest river of Strahler orders 1,2 and 3 (rdist1,rdist2, rdist3) and to all rivers (rdist, Figure 3-12(i)).

Changes of slope also affect the depth of the surface-cooled layer, which is greater on concave rather than convex surfaces, with corresponding lower minima on the concave slopes. For this reason, ARC-INFO commands computing local curvature across and down slope were used to construct further gridded variables (cross, down, slope, curve) although with the realisation that this effect is likely to prove minimal for this study since the average slope of the landscape will be very shallow at the $1km^2$ resolution used.

Local winds

Katabatic winds are mesoscale phenomena (p79) particularly influential in the formation of frost hollows. With the exception of work by Cornford (1997), proxy measures to represent the locations prone to katabatic winds have rarely been derived, or used to improve estimates of local minimum daily temperatures. Owing to their agricultural importance however, considerable effort has been applied to their modelling using process-based techniques (e.g. Laughlin and Kalma 1990). Data problems meant that Cornford's approach, which used land cover data to estimate areas of cold air formation and barriers to airflow, could not be followed. Rather, Tabony's (1985) simpler notion of large-scale shelter was adopted. Tabony suggested that the height of a point relative to the minimum height above the valley base provided a measure of susceptibility to frost. Cornford translated this to the difference between height and the minimum over a 10km radius in his comparative study. In this work, the more process-oriented local drainage basin replaces the geometric radius. Using the ARC-INFO *STREAMLINK* and *WATERSHED* commands, basins of several sizes were generated according to Strahler's stream ordering system. Variables were computed as the height of a cell above the basin minimum (htabovelarge, htabovemid ... htabovebasin, Figure 3-12(e,f)). Cornford's more simplistic algorithm, height above minimum within a rectangular area, was also computed for comparative purposes for squares of diameters 8km and 20km (drop4, drop10 Figure 3-12(l)).

Sea breezes

Manley (1970) observed that '*One of the most notable features of British climate is the extent to which* *incidence of severe frost is mitigated in favourable locations near the sea. The well known principles ... operate very effectively on the steeply sloping coastal margins of Cornwall, Pembrokeshire and the Isle of Mann, as well as on small offshore islands.*' Such qualitative statements are typical of those when searching for evidence as to how far inland the effect of the sea on temperature may remain influential, and also point to the highly localised nature of cliff-side environments. Barry and Chorley (1982, p118) suggest that the sea's moderating influence on both maxima and minima has on average a depth of 1km, but may penetrate 50km inwards. This figure of 50km re-occurs in Linacre (1992, p77). In their European study, van de Goot (1997) places an upper limit of 100km on any coastal effect. Ultimately, the strength of coastal effects is determined by the temperature of the ocean surface upwind and will therefore be affected by the synoptic situation and the season in addition to wind fetch. The complexity of the atmospheric mechanics makes simple linear empirical measures difficult to determine. This suggests that coastal effects should be modelled separately for different directions. Cornford (1997) for example models distance and log distance to the coast in eight directions. However, both he and Lennon and Turner (1995) somewhat surprisingly select isotropic variables following their detailed analysis. In both studies, a ratio of the areal proportions of land to sea within a local search radius proves adaptive to the complexities of the British coastline. Certainly, past evidence with Scottish monthly means suggests that relying on easting alone to account for the coastal effect (Hudson and Wackernagel, 1994) may be inadequate. For this work, distance to the south, east and west coasts are modelled individually (Figure 3-12(b,c)). Gridded variables are also constructed that constrain distance to a maximum of 100km (e.g. east100), and that compute the land/sea ratio over radii of 2 and 5km (pcoast4, pcoast25).

Descent of air from mountains and plateau

Föhn winds occur when a body of air is forced over a mountain barrier. The ascent generated causes the air to cool (at the saturated adiabatic lapse rate, once it becomes saturated) and moisture to condense out, frequently causing rain over the barrier. As the air descends on the lee side of the mountains it will be relatively dry and will warm at the dry adiabatic lapse rate. This means that air at a similar elevation on the lee side of the barrier will be warmer. Cornford (1997) models this effect for Great Britain in eight compass directions, none of which prove significant within his analysis. In this study, only east/west and north/south barriers are constructed, following British discussion of the effect in relation to North Wales and the Pennines (Mayes and Wheeler, 1997, *p25*) and in connection with southerly air flows in particular (e.g. Mayes and Wheeler, 1997, *p35*). Following Lennon and Turner (1995), both the maximum height in the relevant direction only for an unrestricted distance (highsouth, highwest) and that in a 50km perpendicular swathe 25km north and south of the point in question were computed (hightsouth, hightwest, Figure 3-12(j,k)).

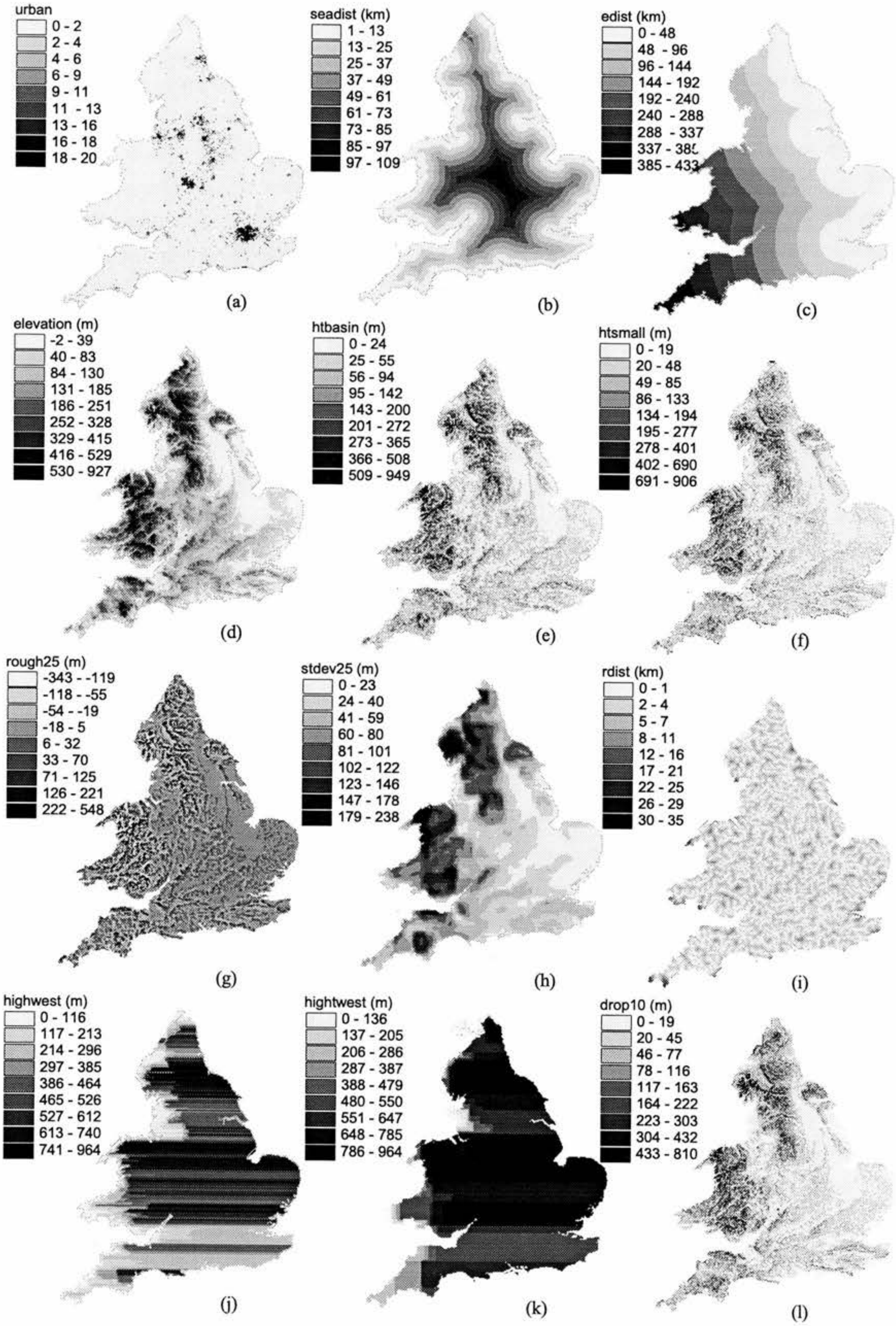

Figure 3-12. Selected guiding covariates

3.3.2.2 Selecting gridded variables

To estimate daily air temperatures at locations intermediate to meteorological stations, using the topoclimatic grids to guide the interpolation, the next step is to develop a parsimonious model from the 'best' of the 36 candidate gridded variables (Appendix 7). Given the multiple daily interpolations required a decision was made to selection one single set of variables, but whose parameters may be adjusted on a daily basis to improve adaptability. The selection of this optimal subset is made complex owing to the large number of possible variables and their inter-correlations. Additionally, exploratory analysis showed the distributions to be strongly non-normal in most cases. However, standard log transforms were not feasible owing to zero values in many of the grids. In his study involving considerably more (88) independent factors, Cornford (1997) selected the most promising variables by eye on the basis of plots of the strength of product moment correlation between the relevant variable and dependent minimum temperature over 152 sequential days throughout the winter period. This approach avoided violating statistical assumptions, but can be criticised as highly subjective. Additionally, it is unclear whether the coefficients used were indeed *partial* correlations. One possibility when faced with such a large number of variables is to compress the data using a principal component transformation. However, it was felt that such a manoeuvre would complicate the later interpretation of variables selected and preliminary explorations indicated that variables did not group by process into distinct components. Given that both Cornford (1997) and Lennon and Turner (1995) found little advantage when principal components or normal transforms of data were incorporated within the interpolations, raw data were used in this study.

In a task with multiple correlated variables such as this, manual iterative regressions in which the user can weigh the effect of alternative substitutions are preferable. However the size of the task was such that, as one component of a broader applied study, only automatic procedures could be warranted. Others, in more theoretical studies such as those of Blennow and Persson (1998) and Lennon and Turner (1995), have adopted a similar approach. Preliminary trials with a subset of factors of low inter-correlation suggested that the 'optimal' model should not contain more than seven to eight variables for minimum temperatures, and highlighted consistent problems of non-linearity in the northing parameter that created the possibility of regular and significant bias in the results. Northings were subsequently log-transformed for all analyses.

Backwards linear regression was used to establish significant relationships between the maximum and minimum temperature data and the pre-processed gridded variables. Daily temperature data from 1986 were used in the analyses, selecting values 5 days apart from the rest in order to avoid problems of temporal correlation in the dataset and so to maximise the information gained. To investigate the influence of the general synoptic situation upon daily air temperature estimates, 21 days for each of the high pressure, low pressure and systems of little pronounced vorticity as grouped by the British 'Lamb' classification were used (Table 3-6). Individual days have been pre-classified by Lamb for the period 1861 to 1997, the details available in the public domain from http://www.cru.uea.asc.uk/~mikeh/datasets/uk/lamb.htm. This use of equal numbers of days for each synoptic pattern, together with the minimum 5-day criterion to limit temporal autocorrelation restriction, restricted the overall data set to 63 days but avoided bias. To minimise problems with correlation between independent variables, the standard tolerance for inclusion in the regression model was increased to 0.15; unfortunately, the facilities of standard packages such as MINITAB and SPSS do not allow this threshold to increase progressively as the algorithm iterates as one would manually. Only variables significant at the 95% level were allowed to remain within the regression equations. The relationships of the gridded topo-climatic variables with maximum and minimum daily temperatures were analysed separately.

Table 3-6. Classification of weather types using the Lamb system

Anti-cyclonic				**Cyclonic**	
0	A			20	C
1	ANE	11	NE	21	CNE
2	AE	12	E	22	CE
3	ASE	13	SE	23	CSE
4	AS	14	S	24	CS
5	ASW	15	SW	25	CSW
6	AW	16	W	26	CW
7	ANW	17	NW	27	CNW
8	AN	18	N	28	CN

The results were compared in terms of the number of times a variable was selected as making a 'significant' contribution to the regression model (i.e. remained within the regression model) and secondly on the basis of the strength of the significant relationships. For the latter, the strength of the standardised beta coefficient was used. This provided a relative measure of the importance of the various independent variables, rather than an absolute one, since its value depends on the other independent variables used within the equation and any inter-correlations between them. A simplified form of parallel co-ordinates charting (Inselberg and Dimsdale, 1994) was used to assist the interpretation of the multiple dimensional results.

```
Rank each list (contribution (a) and strength of relationship (b))
Iteratively, until all variables are ranked:
Is one variable consistently highest ranked?
        Rank next, and eliminate
Else
        Alternately
           [Take highest ranked variable from list a, and eliminate]
           [Take highest ranked variable from list b, and eliminate]
         Re-rank
Endif
```

Figure 3-13. Pareto ranking algorithm

The results, listed on the basis of their significant contribution and strength of relationship when selected, were combined using the 'Pareto' selection algorithm illustrated in Figure 3-13. This reflects the reasoning that while modelling of average temperature conditions is critical to the successful modelling of pest development over a long period, extreme temperatures may cause important thresholds to be crossed that might play a potentially important part in halting or starting development.

For initial experimentation the top 15 ranked variables were highlighted, from which the top 10 covariates were selected having eliminated those with Pearson partial correlations of less than ± 0.5 with any variables of higher rank.

3.3.2.3 Mathematical interpolation methods

The principal guiding variables determined by the regression analysis (p 102) during the first phase of analysis were then used to guide the interpolation of maximum and minimum daily temperatures. During the second 'interpolation' phase of this two-step analysis, the techniques used were chosen because of their common usage in agricultural applications (trend surface analysis, inverse distance weighting) or for their perceived advantages for climatic and phenological interpolations at a variety of spatial and temporal scales (ordinary kriging, partial thin plate splines) (Table 3-7). Trend surface analyses for example are less commonly used within the geographical research domain, but are the default techniques for those interpolating insect phenologies (e.g. Régnière 1996). In order to avoid temporal overlap between the modelling and interpolating phases of the temperature method, the results of interpolations relate to the year 1976 alone.

Given that interpolation has been occupying geographers intellectually and pragmatically for many years, it is perhaps surprising to find that the functionality for this interpolation task within proprietary GIS or provision of dedicated interpolation software packages lags behind other public domain software. Of the functional requirements for this study (Section 3.3.1, p92), one of the more critical elements is the accurate provision of temporal streams of input temperature data to phenological models. As has previously been established (p79), the interpolation of point meteorological data appears the most effective means of meeting this need. While comparisons between methods for interpolating temperatures at a monthly level are now well worked (Section 2.3.3, p55), examples interpolating daily maximum and minimum temperatures at a national level to a $1km^2$ resolution through all seasons are rare. Moreover, different interpolation techniques are rarely compared with a view to identifying their possible contributions to the accumulation of errors over time within the models they serve with data, as in this study. Since insect phenologies are known to be highly sensitive to daily temperatures (e.g. Morgan 1996), apparently small differences within daily results have the potential to become magnified over long model runs.

As Myers (1994) concluded, there is no systematically 'best' performing interpolator. Drawing on the general introduction to interpolation in the previous chapter, the following methods warranted exploration within this study:

- Voronoi tessellation, trend surface analysis and optimal inverse distance weighting;
- Ordinary kriging (GSLIB code, Deutsch and Journel 1992);

- Partial thin plate spline (ANUSPLIN code, Hutchinson 1991b).

The first of these two techniques, Voronoi tessellation and trend surface analysis, are not hypothesised to perform strongly in either mathematical or visual terms. Their inclusion relates to their prior use in this application area: nearest neighbour methods (Voronoi tessellations) for example are implicitly used in much of the applied pest management/modelling arena. In the case of insect phenologies to date, only trend surface analysis and regression functions have been used to interpolate both temperatures (Russo *et al.* 1993) and phenologies (Régnière 1996, Schaub *et al.* 1995b). While a wide range of methods have been used to interpolate temperatures in the theoretical literature (indeed, many methods have originated from meteorologists such as Gandin 1963, Thiessen 1911), most attention has been paid to the climate normal, annual or monthly timescale.

Comparisons between more complex techniques and especially between partial thin plate splines and kriging are more unusual, especially in this application area. Few studies appear to have considered the spatial correlation structures of either daily maximum and minimum temperatures or insect phenologies. The literature on interpolation has been dominated by kriging versus partial thin plate spline debate, yet in no proprietary package may partial thin plate splines and ordinary kriging be compared on their merits for a particular application (Table 3-7). Functions for ordinary kriging are more commonly found, but allowances for anisotropy or warnings over inadequate variogram modelling where necessary are rarely made. Fortunately, a variety of public domain geostatistical software is available (Varekamp *et al.*, 1996). Of these, the quality of GSLIB (Deutsch and Journel, 1992) and VARIOWIN (Pannatier 1996) stand out for research use. In addition, the FORTRAN source code for the partial thin plate spline program ANUSPLIN (Hutchinson 1991b) was made available for this project. The particular advantages and disadvantages of the chosen methods in relation to this particular study are summarised within Table 3-7, and outlined individually in functional terms below.

The inclusion of guiding variables selected using the multiple linear regression process of Section 3.3.2.2 within the interpolation process was implemented without prejudice to any particular interpolation method. Interpolating residuals from the regression analyses (Figure 3-14A) provides a means of incorporating gridded information to enhance inverse distance weighting, and is critical to the success of ordinary kriging where trend exists within the data (p110). These results must subsequently be 're-trended' to construct the final interpolated estimates of temperature. The ability to 'guide' interpolations using linearly related variables is a strong feature internal to the partial thin plate spline technique (p113) but may equally be carried out within trend surface equations. For both partial thin plate splines and trend surfaces therefore, the software allows the incorporation of linear covariates *within* the overall interpolation process (Figure 3-14B). While the differing structures of the interpolation algorithms meant that linear 'guiding' covariates were treated in different ways operationally, in functional terms, their effect was similar.

Table 3-7. Rationale behind incorporation of partial thin plate spline, kriging and optimal IDW interpolation methodologies in addition to the trend and voronoi techniques required for comparison with biological literature

Method	Advantages	Disadvantages	Data requirements
Partial thin plate splines	• Splining techniques expected to produce smooth and visually coherent results, suitable for communicating broad national and regional patterns of pest risk; • Partial thin plate splines allow linearly-correlated spatial data such as digital elevations to guide interpolation, particularly important when data are geographically sparse (Hutchinson 1991a); • Height may be explored as a third independent splining variable to account for frost hollow effects (Laughlin *et al.* 1993); • Fitting parameters may be estimated objectively using generalised cross validation or known average error at data points (Hutchinson 1991b); • Computer code available for the project (ANUSPLIN, Hutchinson 1991b); • Computing load moderate (Hutchinson 1991b).	• Phenologies may be over smoothed, problematic when interpolating at large scales for the purpose of pest control and management rather than national or regional risk assessment for policy purposes; • Splines perform better with regularly spaced data (Laslett, 1994), while meteorological networks are in contrast irregular; • Largely untested for daily climatic variables: may over smooth; • Mathematically, not as sophisticated as regularised tension splines (Mitás and Mitásová 1999): the latter unavailable owing to redirection of GRASS software (Mitásová, pers. comm.). • No spatial estimates of error or variance as standard, although standard error surfaces may be constructed using Bayesian constructs (e.g. Hutchinson and Gessler 1994, Hutchinson 1998).	• The data requirements of partial thin plate splines fall below those of kriging or co-kriging, but the optimal number of observations for interpolating climatic variables on a daily basis at different geographical scales within Britain has not previously been explored; • Extrapolating from work interpolating monthly mean temperatures using partial thin plate splines, it is anticipated that the number of records held by CSL will enable the interpolation of daily temperatures at moderate geographical scales useful for the formulation of pest risk policy.
Trend surfaces	• Computationally simple and quickly processed; • Partial linear correlations can be incorporated within the trend function.	• Locally inflexible; • Cannot use knowledge of local autocorrelation; • May give rise to extreme extrapolated values without modification by associated linear covariates (Collins and Bolstad 1996).	• 'Representative', well spaced data through out England and Wales required; • Data volumes minimal relative to kriging.

Method	Advantages	Disadvantages	Data requirements
Inverse Distance Weighting	• Straightforward in concept; • May provide a useful means of interpolating additional variables such as sunshine hours and rainfall where the principle causes of variation are predominantly synoptic rather than topographic and auto-correlation falls below that measurable using the standard meteorological network; • 'Optimal' IDW, using automatic assessment of weighting parameter, provides greater objectivity than seen in many studies using arbitrary parameters.	• Maintains range of original data values; a problem when the sites of the UK meteorological network are not representative of the overall landscape characteristics; • Have been found to give consistent albeit poor results across a range of temporal scales in a British context for both minimum and maximum daily temperature (Landau 1996); • Does not allow guided interpolation using terrain variables such as gridded elevation except via interpolation of residuals; • Gives visually implausible results unless data volumes are significant when there is underlying trend in data; • Results highly susceptible to the positioning of observations – can produce improbable spatial gradients where data are highly clustered, although mathematical adjustments to the basic algorithm are available (e.g. Shepard 1968,); • Results highly dependent on weighting law applied; • Assumes isotropy.	• Does not require large volumes of data per se, but without them where underlying trend in the data exists may give poor results in both statistical and visual terms; • Given the high spatial variability of sunshine hours and rainfall, factors for which this technique is thought most appropriate, even the full spread of the meteorological network is likely to result in interpolation accuracies below those of maximum and minimum temperature.

Method	Advantages	Disadvantages	Data requirements
Ordinary Kriging	• Takes spatial auto-correlation into account explicitly; • Provides information on spatial pattern and association via the variogram; • Can account for spatial anisotropy within relationships between variables; • Universal kriging also allows the integral modelling of trend using external grids: using ordinary kriging, trend must be eliminated separately (Deutsch and Journel 1992); • De-trended kriging of residuals from regression appears to be a method that minimises extensive modelling of detailed climatological variations under certain synoptic conditions (Cornford 1996); given that such modelling is an expert field in itself, this is highly desirable; • Variograms may form the basis for conditional simulation, which provide the basis for estimating error in the interpolated surface; • 'Optimal' in statistical terms; • In the limited literature on the interpolation of daily climatic variables, de-trended kriging appears the de-facto method in a British context (Landau and Barnett 1996, Cornford 1996).	• Computationally intensive; • Trend within the data must be accounted for explicitly: strict conditions of stationarity must be met; • Co-kriging may be preferable where guiding variables are not linearly related to temperature; • Specification of the variogram can be subjective, both in terms of model form and mathematical parameters; • The automatic fitting of variograms, important within an integrated system for automated processing of daily data, is not recommended (Cressie 1991, Deutsch and Journel 1992)	• Computation of a reliable variogram requires at least 100-200 observations (Webster and Oliver 1992); • For de-trended kriging of climatic variables within Britain, points should be well spaced throughout the country with a range of distances between sites. Local clusters of data at a range of values are also required to model autocorrelation; • The augmentation of this network in a limited region of Britain of similar landscape characteristics to at least 200 observations would allow the detailed exploration of conditional simulation to allow non-smoothed interpolation with error estimates at the local scales needed for the management and control of pest outbreaks.

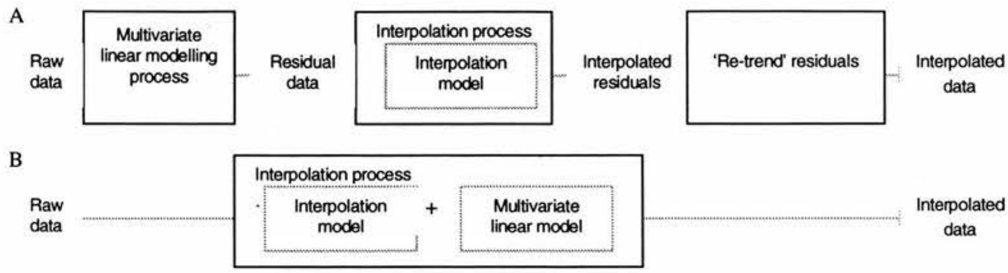

Figure 3-14. Incorporation of linear covariates within interpolation methodologies implemented within GEO_BUG code, A. through the direct use of multivariate linear regression to de-trend and re-trend the data and B. as a central component within the interpolation algorithm itself

The integrated, multi-temporal modelling goal also required that wherever possible, parameters of interpolation models were adjusted automatically. The degree to which this is possible for the individual techniques, and the relative ease with which it may be accomplished were additional important considerations within the following summaries of methods.

The general interpolation functions are summarised as follows (after Mitás and Mitásová 1999). Where a phenomenon z_j exists and there are N known data values of a phenomenon measured at discrete points $r_j = (x_j^{[1]}, x_j^{[2]}, \ldots, x_j^{[d]})$ (in *d* dimensions), then the d-dimensional interpolation function F(**r**) fulfils the condition:

$$F(\mathbf{r}) = z_j \quad j = 1, \ldots, N$$

This represents the *exact* interpolator, and the five methods of interpolation discussed represent a small number of the overall potential solutions that attempt to mimic the underlying phenomenon.

Voronoi tessellation

In mathematical form, this is the most simple function. It may be viewed as simplification of the inverse distance weighting function with parameter a = 1 and data from only one station (the nearest in *d*-dimensional space) is used. As such, any one outlier will have only a local effect.

$$F(\mathbf{r}) = z_{nearest}$$

Trend surface analysis

Trend surface functions commonly form part of the interpolation suite within proprietary GIS software, but usually comprise standard functions relating to the geographical co-ordinates only. In order to incorporate the guiding topographic variables, the concept within this thesis is extended to include additional (non-geographical) covariates. The term 'polynomial regression' is avoided as descriptor since in much of the literature this is used without reference to geographical co-ordinates.

$$F(\mathbf{r}) = \text{geographical trend } (G(\mathbf{r})) + \text{topoclimatic trend } (T(\mathbf{r}))$$

The trend function is a simple linear combination of monomials. Topographic trend (T(**r**)) in this study relates to the incorporation of the multiple topoclimatic covariates using additional linear model functions (Figure 3-14B).

The form of a second order trend with weights a in 2-dimensional geographical space, together with additional d-2 linear covariates, is illustrated as follows:

$$F(\mathbf{r}) = a_1 r_1^2 + a_2 r_2^2 + a_3 r_1 r_2 + a_4 r_1 + a_5 r_2 + a_6 r_3 \ldots a_7 r_d$$

The theoretical literature on the interpolation of geographic data suggests that high order trend surfaces may not produce accurate results, yet within the insect phenology literature, trend surfaces are encountered without discussion. In this case, 2nd order trends were used as the standard method, while 3rd and 4th order models were compared using the best performing covariates as a check.

Optimal inverse distance weighting

The general form of the IDW function used was:

$$F(\mathbf{r}) = \sum_{j=1}^{m} w_i z(\mathbf{r}_i) = \frac{\sum_{i=1}^{m} z(\mathbf{r}_i) / |\mathbf{r} - \mathbf{r}_i|^p}{\sum_{j=1}^{m} 1 / |\mathbf{r} - \mathbf{r}_j|}$$

where m is a number of closest points and p the power parameter representing the decay in similarity between values over distance. In order to incorporate the guiding variables within the analysis, the residuals from linear regression on $\mathbf{r}_j$, rather than $\mathbf{r}_j$ itself as portrayed, were used. The estimator therefore comprised both of linear topoclimatic trend (T($\mathbf{r}$)) plus the IDW function above *on the residuals* (Figure 3-14A).

Drawing on literature that suggests the search parameter (m) to be less critical than the power function (p) (e.g. Hodgson 1993) to the resulting error in interpolated estimates, the Levenberg-Marquandt maximum likelihood function (Press *et al.* 1992) was used to select an automatic power function using a set radius of 12 points as standard. Examples of such automatic parameter setting for IDW are rare within the literature (e.g. Collins and Bolstad 1996). Subsequent sensitivity analyses investigated the adjustment of the search neighbourhood m to include at least 6 and 18 points for confirmation that the radial search parameter did not affect estimates so much as the power function p.

Ordinary kriging (GSLIB code, Deutsch and Journel 1992)

Of the interpolation techniques explored within the study, kriging is the most mathematically complex owing to its stochastic nature. In essence, as with inverse distance weighting, the estimation functions are a form of locally weighted average where the weights are derived following an initial investigation into the spatial structure of the data (variogram modelling). Kriging however, unlike IDW, also takes into account the relative positions of the contributory sample data points. Additionally, the property being estimated (here, temperatures or phenologies) is treated as a *regionalised variable*; that is as a random variable whose variation over space can be regarded statistically. The theory builds on Matheron's premise that properties modelled over space are often too irregular to be modelled by a smooth mathematical function. The random process (in this study, daily maximum and minimum temperatures) at the set of points **x** contains the following components (Cressie, 1991, p113):

Z(x) = (large-scale variation) + (smooth, small-scale variation) + (microscale variation) +

(measurement error)

signal= *(large-scale variation) + (smooth, small-scale variation) + (microscale variation)*

correlated error = (smooth, small-scale variation) + (microscale variation) + (measurement error)

or:

Z(**x**) = *signal + (measurement error)*

Z(**x**) = *(large-scale variation) + correlated error*

This second decomposition forms the basic modelling assumption behind ordinary kriging. In practice, distinguishing between large-scale variation (trend) and correlated error is largely an empirical, operational decision, and there will be no unique split between the two components of the regionalised variable. It will depend instead on the degree to which data are satisfactorily de-trended (in this case, using regression techniques, Figure 3-14A) *prior* to kriging analysis, and the variogram model chosen. This choice, as Cressie (1991, p115) notes, is at present *'a mixture of scientific context, familiarity and intuition'* as demonstrated within the results and discussion of Chapter 4.

Kriging's intrinsic hypotheses (Appendix 8) require that all global trends should be eliminated within a data set before attempting to krige. As for inverse distance weighting therefore, in this study the experimental variograms are constructed using residuals from the regression of temperature with topoclimatic variables. The degree of spatially correlated error is estimated from a sample semivariogram constructed using the given data $z(\mathbf{r}_i)$ and which assumes stationarity:

$$\gamma(\mathbf{h}) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}\{[z(\mathbf{r}_i) - z(\mathbf{r}_i + \mathbf{h})\}^2$$

(where N(h) is the number of pairs of the observations separated) by distance **h**

This is related to the spatial covariance C(**h**) as follows:

$$\gamma(\mathbf{h}) = C(0) - C(\mathbf{h})$$

Given the irregularity of distribution between meteorological sites, it is likely that the sample semi-variogram will be estimated relatively poorly at small distances where the number of possible data pairs is small. As the distance increases, the number of data pairs for the calculation of the semi-variogram initially increases.

Ordinary kriging, implemented within this study, is solved through the minimisation of variance under the assumption that the predictor is unbiased. This second point is achieved by ensuring that the coefficients of the linear predictor sum to 1. Kriging is 'optimal' in the sense that mean square predictor error is minimised in this context. Subroutine 'okb2d' from GSLIB (Deutsch and Journel, 1992) was incorporated within the phenological exploration system in order to implement these kriging functions.

The success of kriging as a technique rests practically on the successful modelling of the variogram

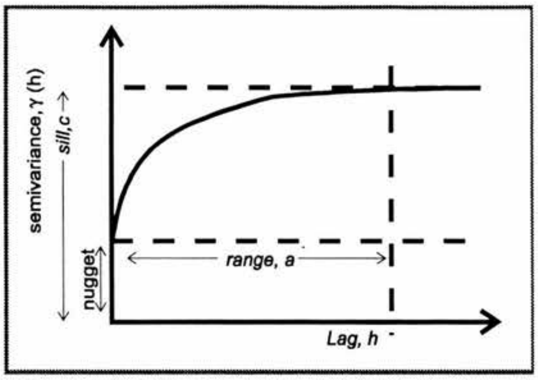

Figure 3-15. Characteristics of the variogram

The success of kriging as a technique rests practically on the successful modelling of the variogram (Figure 3-15). In many cases, this involves estimating up to three features from the estimated curve: an intercept on the ordinate, a portion of increasing semi-variance and a sill. Petkov *et al.* (1996) suggest that the experimental semi-variograms of air temperature, like those of other meteorological parameters, are particularly difficult to estimate since the density of the sample is low in comparison with the spatial frequencies of the main driving factors. One possible ramification within this study is that where underlying trend is not well modelled, variograms may be anisotropic and require computation in two directions. This is quite possible, perhaps more likely, when interpolating phenologies than temperatures given the difficulties of associating phenological results with particular landscape constructs.

In this study, efficient automatic fitting of the variogram is vital since multiple temperature surfaces are required as a sub-component of the wider whole. The *gamv2* subroutine from GSLIB was integrated within the model framework to construct experimental variograms. It has been suggested within the literature that the variogram be computed to between 1/5 (Oliver and Webster, 1990) to ½ (Lamorey and Jabobson 1995, Russo and Jury 1987) its potential length. The maximum lag computed within the study was set to 330km. Further rules of thumb suggest that lags with less than 30 data pairs not be included in the sample semi-variogram fit. The lag distance selected was set at the average nearest neighbour distance, such that this 30-point rule was not broken.

Table 3-8. Examples of common 'authorised' forms of the theoretical variogram

(c - sill, a - range, h - lag distance)

Model type	
Linear	$\gamma(h) = a\mid h\mid$
Power	$\gamma(h) = ah^{\alpha}$
Exponential	$\gamma(h) = c[1 - \exp(-h/a)]$
Gaussian	$\gamma(h) = c[1 - \exp(-3(h/a)^2)]$

Given debate on the advisability of fitting variogram models automatically (e.g. Philip and Watson 1986, Deutsch and Journel 1992, Issacs and Srivastava 1990), an initial set of variograms for both maximum and minimum temperatures under a variety of seasons and weather conditions were computed interactively using the software *Variowin* (Pannatier, 1993). Kelly *et al.* (1998) identified on the basis of long term (1861-1990) data series that the most common Lamb types are westerly, anticyclonic (non-directional) and cyclonic (non-directional) in that order. Over the British Isles, westerlies are most commonly associated with winter conditions, falling sharply during the middle of

November. Cyclonic conditions peak during August. Days from these three groups, within their most common seasons, were used to model variograms for daily temperatures in more detail for:

- Westerlies (Lamb classification 16): 8 January, 19 January, 8 February (1976)
- Anti-cyclonic (Lamb classification 0): 5 September, 8 October, 13 November (1976)
- Cyclonic (Lamb classification 20): 12 May, 1 June, 9 July (1976).

This process was used to set the form of variogram model to be used throughout the model runs. Additionally, the interactive analyses were used to identify whether the use of omni-directional variograms was warranted or whether any directional bias remained within the residuals post multiple regression modelling. This follows Deutsch and Journel's (1998, *p61*) caution that '*good fitting algorithms should require a prior choice of the number of variogram structures, their types, anisotropies, and, only then, the parameters (sill, range) would be chosen to match the experimental variogram values'*.

Both weighted least squares and maximum likelihood functions were investigated for the automatic fitting of variograms within this study. In the case of the weighted least squares option, the weights used are in proportion to the number of comparisons at a particular lag. Where m is the number of comparisons and $\gamma^*(\mathbf{h}_j)$ the semi-variance at lag h, the weighting factor applied was $m(\mathbf{h}_j)/\gamma^{*2}(\mathbf{h}_j)$ after Cressie (1985). Weighted least squares functions were fitted iteratively while maximum likelihood methods were implemented using the Levenberg-Marquardt method for which Fortran algorithms are freely available (Press *et al.* 1992, 678-683). Although local minima cannot be excluded when using the Levenberg-Marquardt method, they are less likely than if using hill-climbing algorithms alone. Given the possibilities of implausible variogram parameters resulting from automatic fitting procedures in the presence of strong autocorrelation on certain days, variogram ranges were constrained to between 300km and 1km following standard recommendations (Oliver and Webster 1990, Russo and Jury 1987).

Using the model form and directions suggested from the preliminary interactive analyses, results from automatic variogram fitting were compared with the models obtained using visual fitting on the specific dates selected, as above. More generally the model fit (r.m.s. error), variogram range and nugget computed using the automatic fitting process were also explored for reasonableness throughout the annual period (1976).

Partial thin plate splines (ANUSPLIN code, Hutchinson 1991b)

Smoothing splines allow a compromise between smoothness and exactness of the surface fit to be considered *together*. In the case of the thin plate splines used for this study linear sub-models are incorporated (*partial* thin plate splines), the coefficients for which may be determined simultaneously within the solution of the spline (Wahba 1990). The partial thin plate spline of methodology of Hutchinson (1991b), unlike the spline functions implemented within proprietary GIS, uses automatic general cross validation to optimise the smoothing function so that over-smoothing does not produce significant departures from the data points. In this case, the $z(x_i)$ are estimated by the (suitably smooth) function which minimises:

$$\sum_{j=1}^{N}[z_j - F(\mathbf{r}_j) - \sum_{k=1}^{p} \mathrm{B}_k \Psi_{kj}]^2 + \lambda I(F)$$

(where λ is the smoothing parameter, $I(F)$ the 'smoothness seminorm' and p the number of partial linear covariates). The smoothness seminorm is a measure of roughness of the function defined in terms of its order of derivative relative to the function (Hutchinson 1991b). Where there is no parameteric submodel (p=0) the solution is an ordinary partial thin plate spline, while conversely without the spline function the system contracts to a linear multiple regression model. Since each parameteric model uses all data points in its construction, the effect of incorporating the topoclimatic variables is equivalent to that achieved by 'de-trending' the IDW and ordinary kriging functions (above). In the thin plate spline seminorm used by Hutchinson (1991b), which depends only on distance and is thus isotropic, this minimisation is subject both to an exactness condition and a smoothing condition.

For the purposes of this study, it is important to note that the generalised cross validation (GCV) used by Hutchinson to fit the spline model automatically is *'a collapsed representation* [of ordinary cross-validation] *which is relatively easy to compute'* (Whaba and Wendleberger 1980). Weights for prediction errors are selected to give more importance to a cluster of points than isolated points, since these are estimated better by their neighbours and are more sensitive to model parameters. While an efficient means to fit individual spline surfaces automatically, because the statistic is only an approximation to standard jack-knife cross-validation it cannot be used to compare the results between the different interpolation techniques.

Table 3-9. Spline models used within experiments

Spline type	Methods
2d	Bivariate spline (easting and northing as independent variables – no additional covariates)
2d	Partial splines (easting and northing as independent variables + n multiple linear covariates)
3d	Trivariate spline (easting, northing and height as independent variables – no additional covariates)
3d	Partial splines (easting, northing and height as independent variables + n multiple linear covariates (height excluded))

This automation of critical parameters within the partial thin plate spline process is important in the context of this study, where multiple surface equations are required. As Hutchinson and Gessler (1994) note when drawing similarities between spline and kriging approaches however (Appendix 4), when splining the set of monomials is determined by the order of derivative minimised: this is user defined, *apriori*. Different orders of the spline equations (2d/3d, Table 3-9) were therefore compared explicitly in this work. In contrast, when kriging it is in general possible to specify the order of drift and monomials separately from the covariance function. This gives kriging more flexibility.

A number of possible spline models were selected for consideration within this work (Table 3-9), both by varying the order of the spline function as discussed and also the number of independent and dependent covariates. A spline model using two variables is known as a bivariate spline, a model with three variables a trivariate spline etc., and the additional variables may be incorporated as independent or dependent (within the partial linear model) factors. The use of splines with more than two *independent* spline variables (e.g. in x, y and elevation) is limited through computational problems, although larger number of dependent variables can be included as partial covariates. On the evidence of Laughlin *et al.*'s (1993) use of trivariate splines where all three variables were independent for modelling frost hollow effects in daily minima, trials of splines were warranted with both two and three independent variables. Elevation was used both as the third 'splining' factor, in comparison with models that used elevation as one of a number of partial linear covariates determined by the regression analyses.

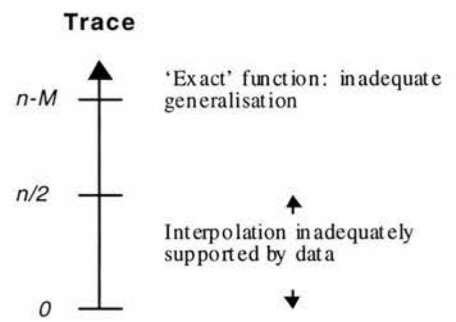

Figure 3-16. The application of trace diagnostics in the analysis of partial thin plate spline results

Statistical interpretation of partial thin plate splines suggests that the trace of the influence matrix can be used as a measure of performance of the technique on a given data set. The trace provides an estimate of the effectiveness of the model, where higher values indicate a good fit. The literature suggests that the trace ('signal') should exceed $n/2$, where n is the number of data points (Hutchinson and Gessler 1994). Where the trace achieves a maximum value of $n-M$, where M is the number of monomials, the fitted spline is simply a least-squares regression of the data on the M monomials (Hutchinson 1994). This exact interpolation implies zero degrees of freedom, with no measurement error or microscale variation. In such cases the function is likely to be over-fitted and generalisation of form lost. Figure 3-16 provides a summary of these issues.

Interpolating calendar data

The majority of phenological outputs within the thesis are computed on the basis of interpolated temperatures, rather than interpolated results from the phenology model run at a limited number of points only. However, the framework allows both possibilities and within Chapter 6 the merits of the two approaches are explored further. In many cases, the results being interpreted may be the Julian dates at which a selected point in a pest's lifecycle is reached. Since calendar dates are circular in value, problems in the way in which data may be interpolated may arise. Potential issues relating to calendar data arise in the case of interpolated phenologies, but have not previously been discussed within the literature despite this being the preferred approach in the limited number of studies to date (e.g. Régnière 1996).

The problem of calendar dates arises typically for a pest outside its normal range. It may happen that the particular point in the pest's life cycle under investigation is never reached during the run period specified by the user. In the context of this study for example, whether a pest is able to reach young adulthood is taken as a measure of how feasible its establishment in Britain might be (Chapter 7). To reach such a stage at any date through the year is a crude indicator of a pest's ability to begin over-wintering, assuming that adequate food is available to allow the start of diapause. In any case when the output from a pest phenology is a date at which a stage is reached, the Julian date result may either be a positive integer (1-366) or a '0'. Zero indicates that the specified development stage and emergence percentage was not reached at any date. However, since a lower (earlier) Julian date normally indicates a *higher* potential for survival than a higher (later) one, the logical direction of the interpolation function is reversed by the inclusion of 0 as a low number indicating *minimal* survival potential.

Two approaches to the problem are to:

- Convert any '0's to a nominal date, say '367' (the data conversion approach, Table 3-10);
- Interpolate phenologies in two phases (the two phase approach, Table 3-10)
    1. Create a probabilistic binary survival mask using indicator kriging;
    2. Interpolate non-zero values only (or with converted data), and mask final results using results from 1.

The advantages and disadvantages of these two options are summarised within Table 3-10. For the reasons tabulated, especially that of simplicity, the data conversion option was implemented. Even with this adjustment however, the range of date values in the resultant grids need to be checked and an upper threshold cut-off applied if necessary using standard GIS map calculation procedures to ensure compatibility with calendar conventions.

Table 3-10. Options for interpolating calendar dates

	Advantages	**Disadvantages**
Data conversion approach	• Computationally efficient; • Simple to implement.	• Choice of substitute value may distort regression analysis e.g. of lapse rates with phenology.
Two phase approach (Indicator kriging)	• Probabilistic survival index a useful tool in its own right;	• Sufficient data to characterise the variogram adequately are required; • Added programming and computational complexity; • The margins of development may be distorted within the Julian date grids when only points where survival is feasible are used in interpolation.

For indigenous pests, within their environmental margins of development the issue is likely to be less acute. This may explain why previous work (Schaub *et al.* 1995b, Régnière 1996, Russo *et al.* 1983) has not addressed the issue.

3.3.3 Assessment of estimation errors in climate and phenology results

3.3.3.1 Error modelling

The working rationale that minimising input error is a neglected factor in reducing overall modelling uncertainty relative to that of the biological models themselves is an important component of the study requiring investigation.

Omit single point from analysis

De-trend remaining data

Create interpolation surface equations/parameters using remaining data

Interpolate temperatures/phenology to site of missing data

If temperature, run phenological model with site estimates of temperature

Compare 'actual' temperature/phenology for omitted site with interpolated estimates

Square difference in temperature/phenology and add to sum of differences

Return omitted point into subsequent analysis

End

cross validated error = sqrt (sum of differences / no of points)

Symbolically:

$$T_i = f(T_1, T_2, ..., T_k, ..., T_n)$$

$$P_i = f_a(f_b(T_1, T_2, ..., T_k, ..., T_n))$$

Where:

T_i are temperatures, P_i are phenologies, f_a represents the phenology modelling function and f_b a particular interpolation method.

Figure 3-17. Jack-knife cross-validation strategy

Semi-independent cross validation techniques such as the jack-knife and bootstrap have been a popular means of assessing statistical estimation and prediction since the mid 1970s (Cressie 1991, p101). As noted within Section 3.3.3 (p117) jack-knife cross validation was selected for validating maximum and minimum temperature results. For this study, jack-knife cross validation is also adopted to provide a measure of modelling accuracy that is able to track errors as they are propagated through the modelling system (both interpolation and biological model) throughout a model run. Jack-knifing refers to the practice of removing data points singly and using the remaining data to predict the values at the deleted points (Figure 3-17), and contrasts with bootstrap methods where multiple points are removed at any one iteration. Iterated, this allows some measure of the overall prediction error to be estimated. Adoption of this technique allowed the tracking of error at any temporal time step within the modelling process, both in terms of the input data error *and* the resultant phenological model inaccuracy (Figure 3-17), albeit at selected data dependent points within the landscape. In this way, the effect of interpolation error propagated through the phenology models at each stage may be investigated. In contrast to the use of insect trap data to validate models at a single point in their life cycle (e.g. Schaub *et al.* 1995b), this use of cross-validation allows the partitioning of interpolation error from biological modelling error since, when using cross-validation, errors of biology are assumed negligible. The variation in results arises rather from the error in the estimated geographical inputs alone. This strategy for error modelling required that an identical network of temperature data was used from day to day.

The process of cross-validation results in an estimated model value for each point sample location, which may then be compared with the known value at that point. Throughout this work, the term 'residual' is taken to imply the remainder when the estimate is subtracted from the known value. The significance of the model fit may be explored just as if comparing truly independent data with modelling estimates, with a similar range of statistical options. Some authors use the correlation coefficient derived from comparing actual and predicted data (e.g. Landau and Barnett 1996). This has the advantage of being size neutral, but may mask overall degree of spread in results. Mean square errors (m.s.e.) and root mean square error (r.m.s.) are more widely used (e.g. Hutchinson 1998), and the r.m.s. error was favoured for this study owing to its greater sensitivity to outliers and thus greater rigour. A unitless percentage r.m.s. error is also introduced that will be used to compare errors from interpolation in a manner that is independent of the actual values interpolated. In addition to the mean value of all residuals (bias), the spread of errors was computed using standard deviation and variance statistics. In summary:

Bias = Σresidual

Residual = actual – estimated value

Root mean square error (r.m.s. error) = $\sqrt{((\Sigma \text{ residual}^2)/ n)}$ where n is the number of points

% r.m.s. = $\sqrt{((\Sigma \text{ ((actual-estimated value)/actual value)}^2)/ n)}$ where n is the number of points

Inspection of these performance parameters together will enable a measure of the bias, precision (r.m.s. error) and accuracy (residuals) of the modelling results to be estimated.

Within the geographical literature, cross validation errors have been mapped as 'glyphs' superimposed upon interpolated surfaces (e.g. Mitás and Mitásová, 1999) and have also been themselves interpolated to provide an 'error surface' (Robeson and Willmott 1993, Lennon & Turner 1995). However, as noted within Chapter 2, their variation over time has rarely been considered beyond their use in the production of error 'glyphs' side by side for two different time periods as a by-product of interpolation (Mitásová *et al.* 1995). The method proposed in Figure 3-17 is novel in comparison since it allows a full exploration of the manner in which input errors accumulate over time in terms of the resultant phenological accuracies.

The provision of full error surfaces would be a valuable addition to any geographical study. 'Spatialising' error through an empirical procedure such as interpolating residuals is an attractive concept when considering computational efficiency in comparison with time-consuming Monte-Carlo type error analyses, especially given the national coverage in a study such as this. In support of this goal, the efficacy of interpolating residuals will be explored in Chapter 5 (Section 5.3.4) from a critical viewpoint. The question arises however that *if* the representation of both spatial autocorrelation and underlying process is optimal given the available data in the original model, then why should any interpolatable trend or local spatial autocorrelation be identifiable within the residuals? This line of argument does not appear to have been fully pursued in the research literature to date.

3.3.3.2 Independent validation of spatial insect phenologies

True validation for the purpose of pest management in particular requires an understanding of both interpolation error and biological modelling error in combination at those stages of the life cycle pertinent to potential users of the system. Independent test data may be available for input data series (maximum and minimum daily temperatures), for laboratory tested phenology models and at selected times or target events for indigenous pest development. However, actual outbreak data to validate the 'fully spatial' outputs will inherently be lacking for non-indigenous pests. One reason for selecting codling moth (indigenous to England and Wales) was the prospect of using actual trap data as an independent test of the model results for 1976, averaged over the 1km^2 modelling resolution. Unfortunately, while trap data for the test year (1976) was theoretically available, it proved to be inadequately spatially referenced: an indication in its own right of the historical lack of geographical consideration within pest management.

3.3.4 Integration of interpolated data and biological models

As developed within Section 2.3.1 (p48), integration and operability issues have formed a substantial part of the literature on GIS and environmental modelling over the past few years. Such concerns relate both to the flow of data between components of a linked modelling system in order to make spatio-temporal processing feasible (e.g. Fedra 1993, Abel *et al.* 1992, Downs and Priestnall 1999) and more recently in terms of the underlying compatibility of spatially referenced data from different sources within the context of 'Open' GIS (e.g. Abel *et al.* 1998).

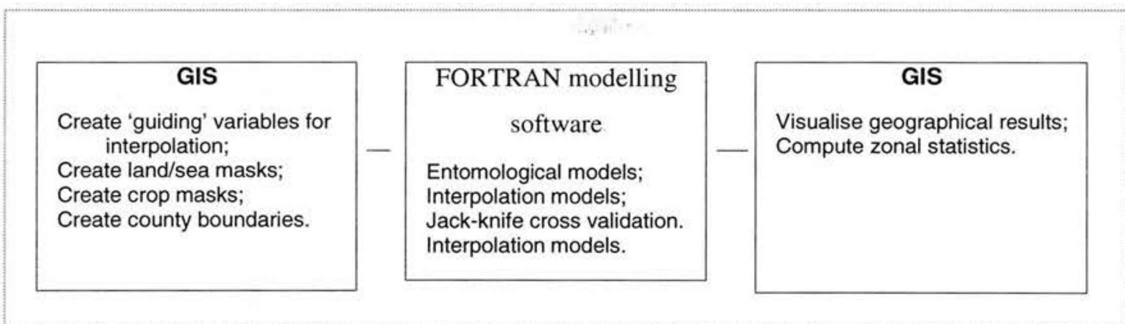

Figure 3-18. Relationship of GIS and dedicated modelling software

Major proprietary GIS allow system calls to be embedded within a macro environment, raising the possibility of linking external models within a GIS environment. However, discussion has shown that a full and flexible set of interpolation functions is often absent from such packages. Moreover, the relative computational inefficiencies of interpreted macro code for environmental modelling purposes are also well known (e.g. Dragosits *et al.* 1996). When modelling at a national level and over multiple time steps, this inefficiency was expected to become pronounced. For example, pilot cross-validation tests carried out as part of this study within ARC-INFO™ on the effectiveness of interpolation techniques on single temperature surfaces alone took days to complete.

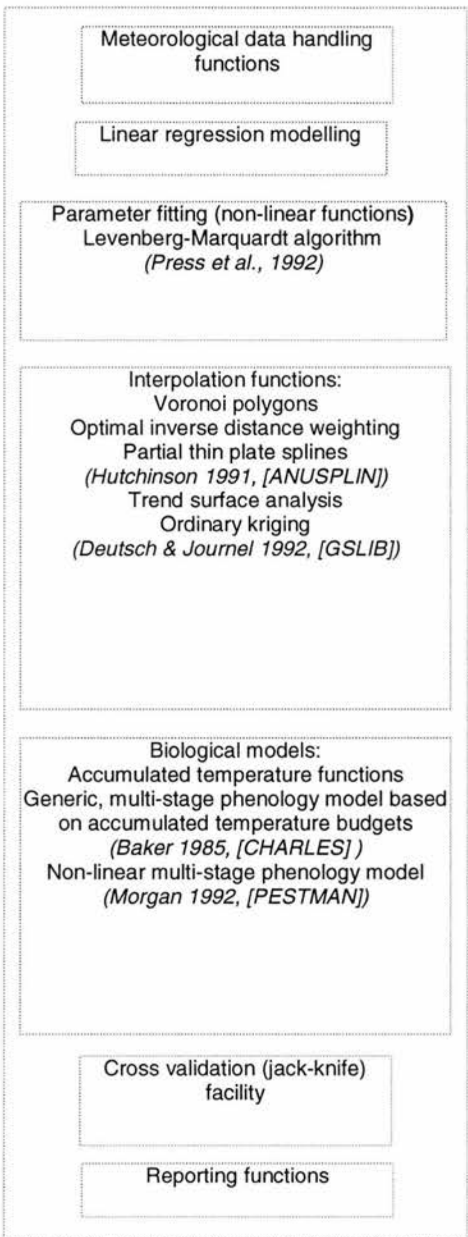

Figure 3-19. Software components and attribution

Historically, the public domain GRASS system has been an exception among GIS systems in providing low level support for multiply linked applications and the software base of choice for environmental modellers. Moves towards more 'open' proprietary GIS during the lifetime of this work have meant further developments in this environment have slowed, while those in proprietary GIS have not progressed fast enough to enable efficient spatio-temporal data management. In particular, from a technical perspective the incomplete move from integer to floating point versions of the GRASS software created an unstable platform on which to develop an integration strategy. Of particular pertinence to this study, the semi-completed redesign of sophisticated spline interpolation routines (e.g. Mitásová *et al.* 1996) to this new model in conjunction with political changes in US GIS strategy (Mitásová, pers. comm.) removed a strong advantage in remaining within a tightly coupled GRASS GIS environment. For these reasons, GIS have been used only to pre-process (GRASS/ARC-INFO™) and post-process (ARCVIEW™) modelling results from code written in FORTRAN (incl. ANUSPLIN (Hutchinson 1991b), GSLIB (Deutsch and Journel 1992)) in a classic example of 'loose coupling' (Figure 3-18).

The modules required to fulfil the functional requirements of the study, which draws on a variety of public domain FORTRAN 77 software together with hand coded modules and linking elements, are illustrated within Figure 3-19. Given that the chief function of the framework is to enable an exploration of phenologies, coding details are avoided here. Rather, program and subroutine titles are listed within Appendix 11.

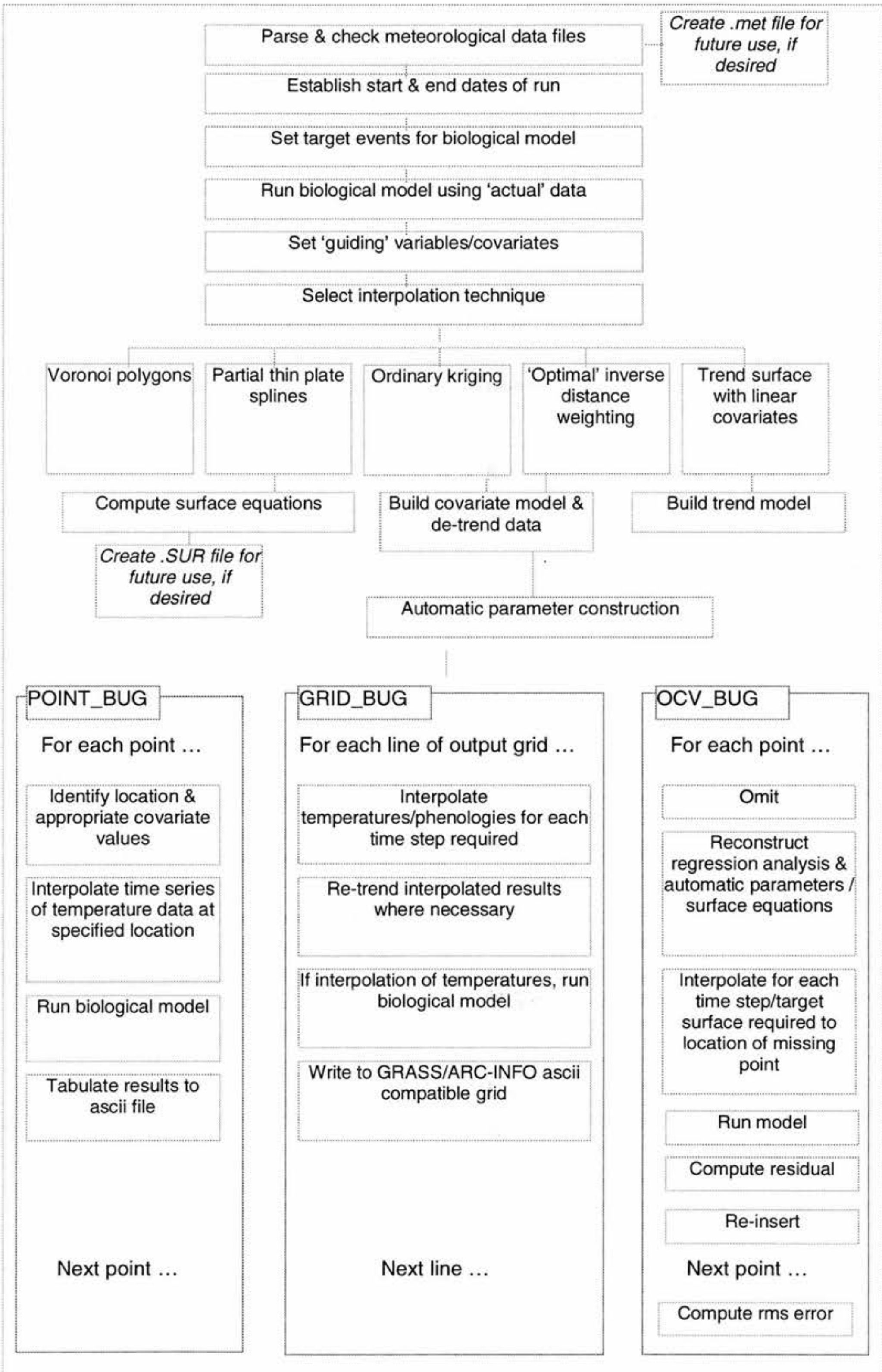

Figure 3-20. Program components and flow of data and control in the spatial phenological modelling system (GEO-BUG)

Seven major components of the software framework may be identified within Figure 3-19. Given the unusual volume of meteorological data used within the research, meteorological data handling functions form an important if largely hidden role. Many other applied studies requiring meteorological data for example focus upon monthly inputs, for which the volume of data is reduced approximately 30-fold.

The functions coded within this first part of the system are used to extract and pre-process data from a database of meteorological information (which includes multiple variables, ordered by UKMO station number) according to the length of model run required. Data are subjected to quality checks, and missing data may be infilled as discussed previously (Section 3.2.1, p87). This module also matches station locations with their appropriate landscape characteristics for use in guiding subsequent interpolations. The second component facilitated within the research software is the ability to 'de-trend' either climate or phenological information using multiple linear regression prior to interpolation, discussed within Section 3.3.2 (p104).

The core element within the research software suite is the implementation of a number of interpolation methods, as outlined above (Figure 3-19). Implementation of the more sophisticated methods draws on existing FORTRAN code supplied by Professor Hutchinson and the public domain code of Deutsch and Journel (1992). The more straightforward techniques (trend surface analysis and inverse distance weighting) were hand-coded. Rarely is this combination of interpolation techniques encountered within one framework. The ability to compare directly the results from both partial thin plate spline and ordinary kriging interpolation, both used separately for climate applications, is particularly unusual. The automatic selection of interpolation parameters for inverse distance weighting, spline and kriging analyses forms a critical element of the system since the manual assessment of daily parameters for model runs of up to 1 ½ years is infeasible. The day to-day fluctuations within the parameters selected for modelling daily temperatures will be reported within Chapter 4 to assess their consistency. The working assumption on programming the software was that, given the variability in British weather, parameters will vary frequently and that the accuracy of daily interpolations would be reduced if fixed coefficients were used for every day of the model run.

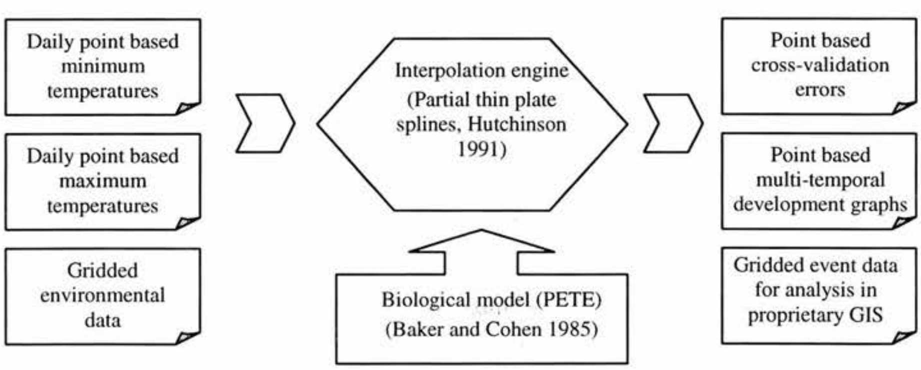

Figure 3-21. GEO_BUG, an interpolation engine to link point temperature data with temperature dependent biological models

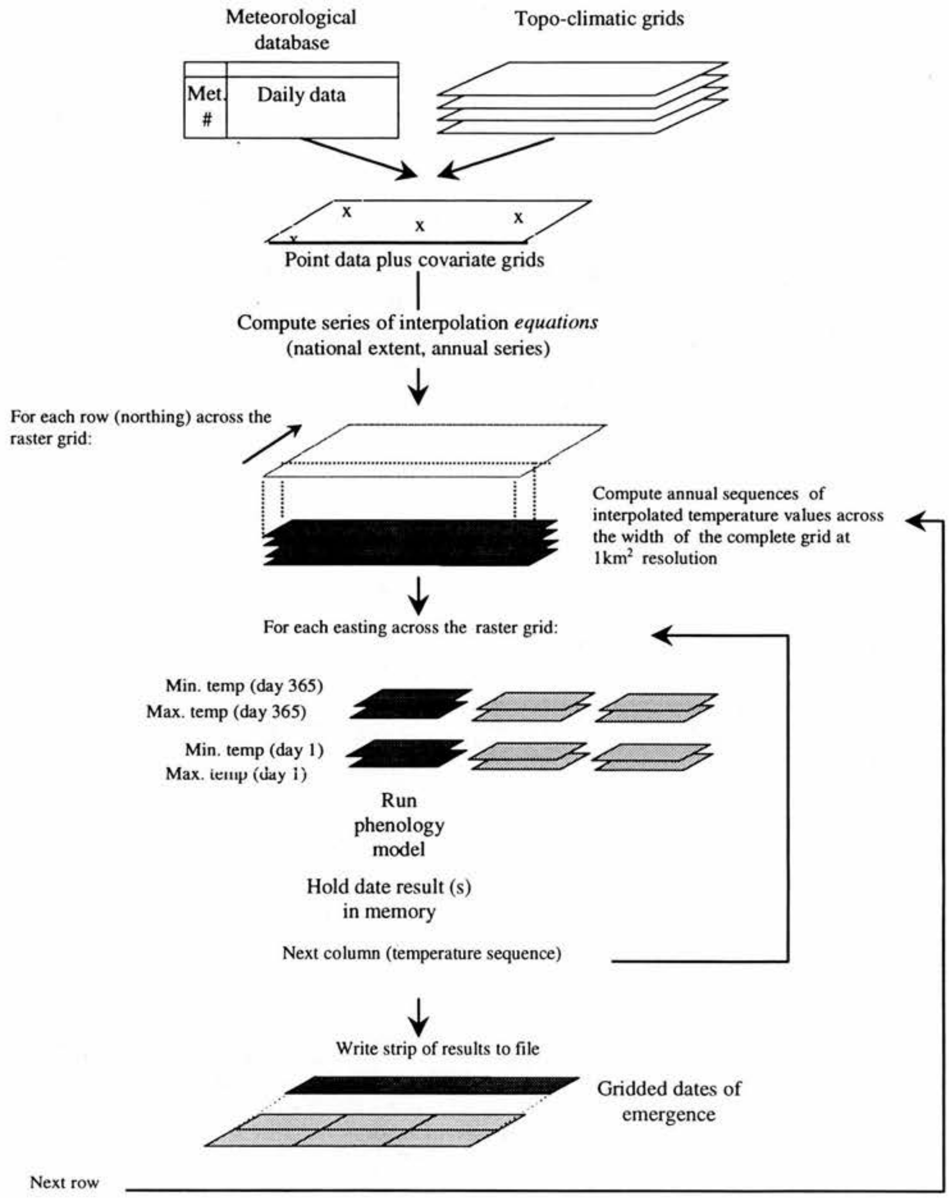

Figure 3-22. Flow of spatial data

Fundamental to the research goals was the ability to link biological (phenological) models directly with the interpolated data at multiple time steps. The individual models linked within the system for the purpose of experiments reported within the thesis were discussed individually within Section 3.1, each of which were supplied to the project as raw FORTRAN code. In order to allow multiple pests to be explored, a standard framework has been created for the integration of different phenology models, beyond those introduced within Section 3.1. Individual model subroutines may be compiled under the name 'bio-model', so allowing a relatively generic system with flexible output types and numbers. The conceptual nature of this facility is illustrated within Figure 3-21. Models now linked within the framework, but not reported within the thesis, include for example a potential *Bemisia tabaci* population model (a non-indigenous glasshouse pest currently confined within greenhouses) and a vine weevil population model (one of the most widespread horticultural pests in Britain together with data from overwintering experiments. Sequences of outputs on a daily basis may also be explored using movie type techniques (e.g. Morgan and Jarvis 1999).

As discussed within Section 3.3.3.1 above, cross-validation provides a means of assessing error both within individual data layers and additionally its accumulation over time when propagated through the phenology models. The relative ease by which these estimates may be made was facilitated by the specific program structure (Figure 3-20), which explicitly separates the processes of building of an interpolation model and the construction of the interpolation grid itself. The ANUSPLIN software in its original form forces this distinction by separating software modules, as does the use of separate packages such as VARIOWIN (Pannatier, 1996) for variogram modelling and GSLIB (Deutsch and Journel, 1992) for kriging. Neither however use this as an explicit means of enabling sequences of temporal data to be efficiently interpolated in space. This facility makes the computation of errors using cross validation feasible (program *OCV_BUG,* Figure 3-20) since estimates for individual locations in space may be computed rather than those for the entire interpolation space as within proprietary GIS such as ARC-INFO™. The use of a consistent temperature network from day-to-day, vital in allowing the consistent use of jack-knife cross-validation techniques through model time sequences also improved the computational efficiency of the software.

As intermediate outputs, interpolated temperatures (for all modules) may also be accessed in addition to the phenology results. The same elements of program structure that allow the efficient computation of jack-knife cross-validation statistics also contribute to a variety of reporting options. Results for potential pest development at any point within space through time (program *POINT_BUG,* Figure 3-20) may be computed, mimicking traditional phenology model outputs (Figure 3-5, Figure 3-7) but with improved spatial precision.

Additionally, the structure facilitates the streamlined production of gridded phenology outputs (*GRID_BUG,* Figure 3-20) by means of the mechanism described within Figure 3-22. This demonstrates the approach taken to spatial data handling within this study. The creation of multiple surfaces for the entire study area to be held in memory throughout the entire phase of biological modelling would be required using proprietary GIS e.g. Arc/INFO GRID. In contrast, the software designed for this project interpolates a time series of temperature data for the annual sequence *but only for a thin strip of cells at a time* (1km wide) across the country. Modelling throughout the time period is carried out for each grid square in turn, the primary spatial result(s) for that swath then written to ascii input grid(s) in a format that conforms with the requirements of one of two proprietary GIS (GRASS or ARC-INFO™/ARCVIEW™).

The number of options, and flexibility to choose different interpolators and measure their jack-knife cross-validated error, available within the pest phenology exploration system marks it out as research oriented software. For example, the system provides the ability to interpolate either model outputs or multiple data inputs, an issue raised within Section 2.3.2 (p50) as a subject rarely investigated within a GIScience context and reported within Chapter 6. Additionally, the system is 'command-line' driven although UNIX scripting languages were used to create efficient run-time 'macros' for the many experiments (temperature and phenology based) throughout the thesis. For operational use, 'optimal' procedures would need to be pre-selected for the user, who might focus rather on the specification or exploration of the effects of biological modelling parameters on the results over space and time using a carefully designed user-interface. Early explorations to this end have been made by Gillick (1998) in a linked study which investigated the development of a pest risk assessment oriented interface to this interpolation and modelling framework.

3.4 Summary

The basic methods by which phenology models may be linked with interpolated temperature values to produce spatial phenologies have been discussed within this chapter. Methods for interpolation were introduced as general concepts, and the particular strategies adopted for the interpolation of daily maximum and minimum temperatures were outlined (Section 3.3). Additionally, Section 3.3.3 provided an important focus on questions of error assessment.

The structure outlined provides a basis for exploring a number of research issues in GIScience and insect ecology which, given the focus in previous work on the building of locally relevant, practical management tools issues, have yet to be explored thoroughly. Within the following chapter, the results of the two-step interpolation of temperatures are discussed. These interpolations provide the basis for the subsequent modelling of the geographical phenologies which form the basis for discussion within Chapters 5 onwards. These later chapters will draw upon the understanding gained within this chapter regarding the interpolation methods used, the nature of the insect lifecycles and typical phenology outputs, and the manner in which errors are assessed for individual surfaces and propagated through the models using jack-knife cross-validation. These general methods will be supplemented by task specific methodologies introduced on a chapter by chapter basis, that introduce additional error metrics (chapter 6) and risk indices (chapter 7) and comparative experiments (chapter 5, chapter 7).

In closing this chapter, it must be stressed that a complete pest risk assessment or pest management plan covers a variety of further issues in addition to the specifics discussed here. In particular, an operational PRA or IPM assessment relies on expert biological knowledge and interpretation of all model results. Given the spatial scale at which modelling in this study will take place ($1km^2$), the spatial phenologies developed represent local averages and are therefore best used to make *relative* comparisons as opposed to absolute levels of risk between locations and over time. It is thus most suited to the modelling of the potential development of non-indigenous pests. As Walker and Young (1997) note, '*Policy makers need to identify strategic outcomes likely to occur as a result of their*

***decisions; they seek timely systems that are generally right about issues of importance rather than systems precisely right about detail.*'** General issues about the use of locally relevant input data for IPM will also be covered as part of chapter 7. Only with further consideration of microclimate and sub $1km^2$ temperature variations could the geographical framework be re-positioned as a tactical rather than strategic tool to provide support as part of a modelling effort to consider the likelihood and spread of a non-indigenous pests, or the dispersion of well established indigenous organisms.

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4 The interpolation of daily air temperatures: results

4.0 Introduction

This chapter reports on the results of interpolating daily maximum and minimum temperatures over England and Wales. The issues discussed include:

- The relative success of the relationship between derived topo-climatic variables and daily maximum and minimum temperatures (based upon data from 1986);
- The consistency of the automatically derived parameters for the interpolation methods;
- The effect of increasing numbers of guiding covariates on interpolation accuracy, for trend surface analysis, partial thin plate splines, inverse distance weighting and ordinary kriging;
- An evaluation of the 'best' interpolation technique for the purpose of interpolating maximum and minimum temperatures in the context of this study, for use in subsequent phenological explorations.

Methods for evaluating interpolations vary considerably within the literature. Franke (1982) suggests for the general case that interpolations be evaluated according to their visual appropriateness, computational efficiency and numerical accuracy. The most common approach for temperatures is the quantitative approach. Interpolation results in this chapter are presented from a number of perspectives:

- Daily r.m.s. error, computed using residuals (actual – estimated temperature) averaged for the year 1976;
- Daily variations in r.m.s. error throughout 1976;
- Visualisation of the averaged spatial pattern within daily residuals (actual – estimated temperature) over the annual cycle for both long term mean residuals and the variance in residual at particular locations over the annual period of 1976.

Given that the size of the initial data set available for this study (174 points over England and Wales) was towards the minimum appropriate for adequate variogram construction, residuals computed using jack-knife cross validation (Figure 3-17) were used to construct all the error statistics throughout this chapter. A subsequent tranche of 120 test data enabled a late comparison to be made between accuracies computed using jack-knife cross-validation and actual independent test for the 'best' interpolation method as determined here. These findings will however be reported separately within Chapter 5 (Section 5.3.3).

4.1 Results

4.1.1 Topoclimate

4.1.1.1 Consistency of selection

Results indicating the consistency (number of days/total 63 days for which the variable provides a significant contribution to explaining temperature) with which guiding variables were included as significant within the modelled regressions are graphed by weather type for (a) maximum and (b) minimum daily temperature in Figure 4-1. As might be anticipated, a smaller number of variables were selected more consistently over the 63 days analysed and with less variation according to weather type for daily maximum than for daily minimum temperatures.

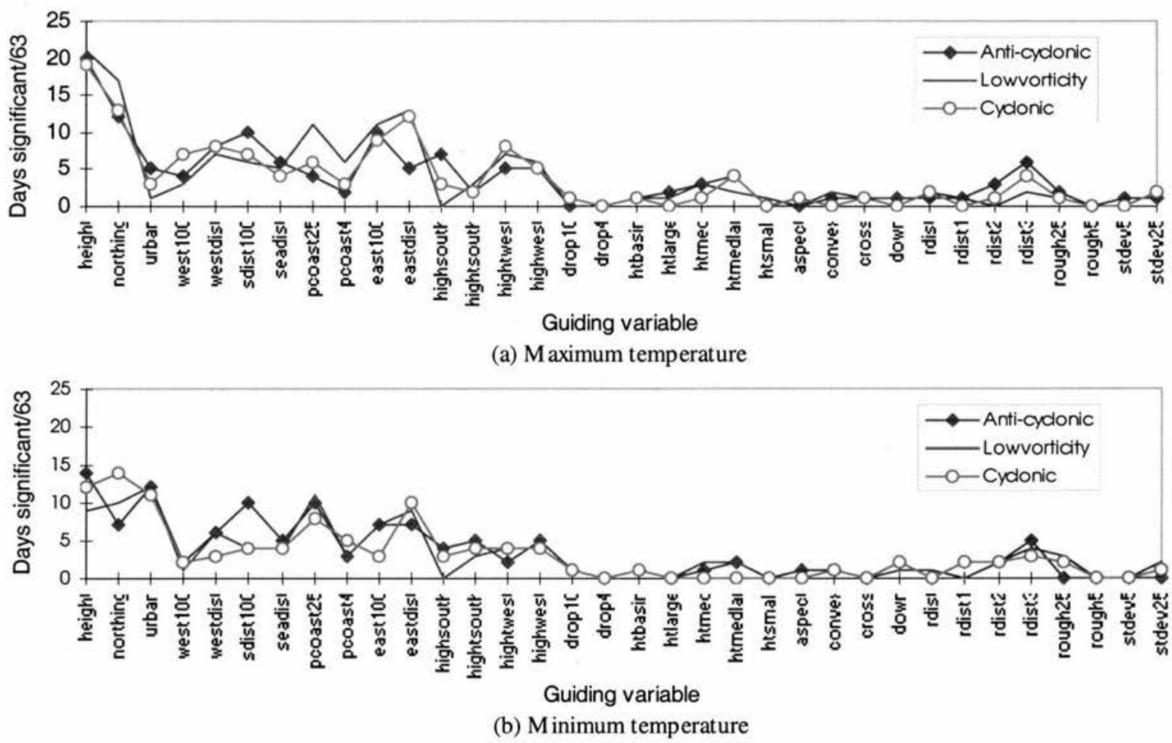


Figure 4-1. Consistency of selection of topo-climatic and land-cover related variables, (a) daily maximum and (b) daily minimum temperatures, 1986

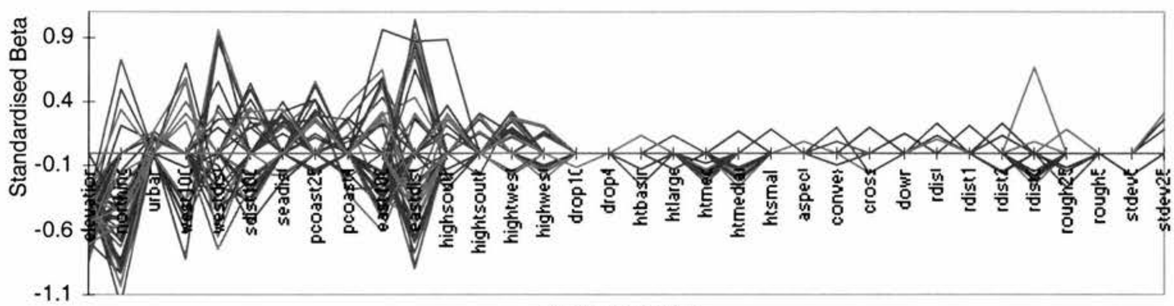
While elevation, presumably through the lapse rate effect, was found to be an important variable and was selected for both maximum and for minimum temperatures, its dominance is greater in the case of estimating maxima (Figure 4-1 (a)). For maximum temperatures, the urban index variable is rarely selected. The effect of northing appears considerably more influential for estimating maximum temperatures than minima under all conditions but particularly under conditions of low vorticity. Directional coastal influences prove more influential than non-directional indices, such as the land/sea ratio, for all directions with distances to the east coast most commonly selected as significant. Also in the case of maxima, measures relating to the maximum height to the west are more consistently chosen, with the broader north-south banded index (hightwest, Figure 3-12(k)) of greater significance than its more restricted counterpart (hightwest, Figure 3-12(k)). Distance to the nearest river and height above the medium-large basin within which a site lies were less often chosen and slope related variables were of little influence at this $1km^2$ scale.

In the case of minimum temperatures, three main variables dominate Figure 4-1 (b). These are the effect of elevation, northing and the urban index, which are all significant (95% confidence) on approximately 12 days of the 63 modelled. The effect of the northing variable was found to be less important for estimating minima under anti-cyclonic conditions, when there is a corresponding increase in the contribution for the distance from the south coast (sdist100, maximum distance 100km). Similarly, elevation was less frequently selected under weather conditions where there was no pronounced vorticity. Exploratory analysis revealed that the effect of northing upon temperature estimates was commonly non-linear, and for this reason log northing is used throughout this analysis. A further important group of variables providing consistent significant contributions to the regression equations relates to the coastal aspect of the meteorological sites. Directional variables are consistently selected more frequently than the simplest 'distance from the sea' measure, with distance from the east coast (unlimited or constrained to 100km: edist, edist100) of greatest influence. Indeed, in combination, the influence of these coastal effects regularly provides a greater contribution to explaining minimum temperatures than elevation. Of the variables measuring the local ratio of land/sea, effects up to 25km (pcoast25) were found to have influence on minimum temperatures more often than those extending to 4km only (pcoast4). Pcoast25, of all the coastal variables, is consistently the most dominant under all weather groups over these 63 days for minimum temperatures. Other indices that were less consistently significant (only 5 days) were maximum elevation to the west and south (the latter not under conditions of low vorticity, however), height above the base of a 'medium to large' valley and the distance to a river, whatever its size. Slope and aspect related parameters such as concavity, convexity and aspect were rarely selected. Under conditions of low vorticity or low pressure, variables relating to surface roughness (rough25 and stdev50) were selected only occasionally.

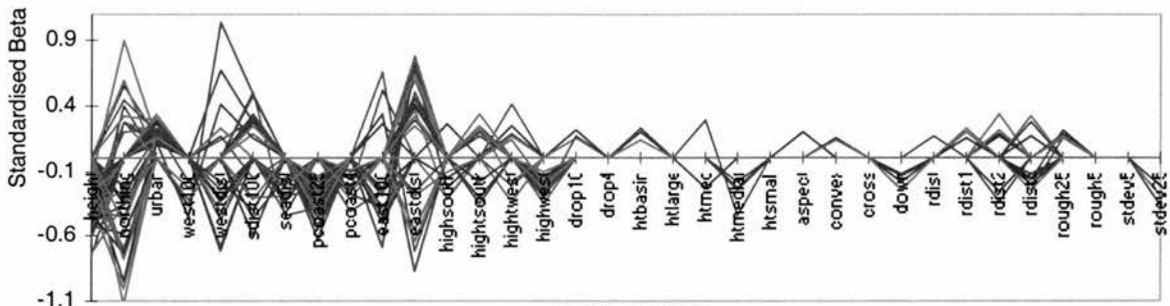
4.1.1.2 Strength of relationship

The relative strength and direction of selection for each of the 63 days modelled is represented by a parallel co-ordinates plot of the standardised beta coefficients for all variables (Figure 4-2). The relationships were found more muted for minima, as was the case for the consistency of selection (Figure 4-1).

In the case of minimum temperatures (Figure 4-2(b)), elevation, northing, west and east coastal influences had stronger relationships when selected as significant variables. Elevation exerts a negative influence over minimum temperatures, with standardised betas falling largely between -0.6 and -0.4. The 'standard' lapse rate is commonly accepted to be 6°C per 1000m, although this is known to vary throughout the year (e.g. Bolstad *et al.* 1998). While in the correct order of magnitude, the modelled average falls slightly below that expected. This suggests that the manner in which cold airflows are accounted for could be improved. The direction of relationship in the case of northing is less clear, with high values of beta (both positive and negative) under cyclonic conditions and smaller beta coefficients under conditions of low vorticity. Coastal influences also exert strong effects on the regression relationships, especially under anticyclonic conditions, with the direction of the relationship altering according to season. Under such weather patterns, temperatures increase sharply with increasing distance from the east coast in the summer season in particular. For both the urban index and land/sea ratio, both consistently selected for minimum temperatures with consistent betas between 0.2-0.4 and -0.3--0.6 respectively are found between weather groups although both are most influential under conditions of low vorticity.



(a) Maximum temperature



(b) Minimum temperature

Figure 4-2. Strength and direction of relationship between topoclimatic variables and (a) daily maximum temperatures, (b) daily minimum temperatures for each of the 63 days analysed, 1986 (blue – anticyclonic, green – low vorticity, red - cyclonic)

Variables designed to reflect the degree to which large scale topography provides a shelter from prevailing weather systems (hightwest, highwest, highsouth, hightsouth) in contrast show relatively insignificant relationships with minimum temperature. In the case of the variables chosen to incorporate a broader 'barrier' concept (htwest especially), their effect was to reduce minimum temperature with increasing elevation to the west for all weather types. Turning to the impact of basin shape on estimates of minimum temperature, both height above the minimum elevation over a $10km^2$ area and height above the most local basin exert positive influences in minimum temperature under all main weather groups. For anti-cyclonic conditions, the height above the base of the larger valley within which a site lies was negatively related to minimum temperature. Increased local surface roughness decreased the intensity of minima, while variability over a wider area was associated with lower minimum temperatures.

Turning to maximum temperatures (Figure 4-2(a)), the significance of individual variables with temperature shows a similar but often inverted pattern to those for minima. The relationship between maximum temperature and elevation shows a more consistent and slightly stronger negative relationship than for minimum temperatures. Distance from the west coast shows a strong but bipolar relationship with maxima, the cause of bi-directionality attributed to seasonal differences between land/sea heat accumulation. Under conditions of low vorticity however, the predominant emphasis is for temperatures to decrease strongly with distance eastwards with the reverse situation occurring under anti-cyclonic and cyclonic conditions.

4.1.1.3 Topo-climate: combining the evidence

The importance of elevation, through the standard atmospheric lapse rate, is well documented and its consistent selection for both maximum and minimum temperatures was to be expected. In terms of the overall number of days on which this variable was found significant at the 95% level however, this was lower than anticipated (Figure 4-1). Under the relative stillness of anti-cyclonic weather, the lapse rate effect holds more consistently. In part however, this unexpectedly low selection of the elevation variable may reflect the strong degree of cross-correlation between a number of individual variables, which have been incorporated to encapsulate different types of process. The negative relationship between the height above the base of a medium large basin (htmedlar) and minimum temperature (Figure 4-2) suggests that such variables are acting, on occasion, more as proxies for elevation rather than representing the effects of cold air drainage as intended. This is one of the drawbacks of the automatic regression approach used, where individual variables may be selected rather than *combinations* of more appropriate variables (from a perspective of process) which together form significant groups. Tailoring groups of variables specifically for individual weather situations, rather than choosing from a wider range of variables on the basis of empirical relationship alone, might assist in avoiding this situation.

The northerly influence is also strongly influential for both maximum and minimum temperatures, both in terms of consistency of selection and strength of relationship. Given Linacre's (1992, p77) rule of thumb suggesting a 5°C difference between the north and south of Britain, this is unsurprising, and relates to a large degree to be curvature of the earth and overall solar aspect. The non-linearity encountered within this relationship may be a result of prevailing weather systems being distributed unequally across the country. A further cross-correlation is evident between distance from the south coast (sdist100, limited to 100km), chosen to reflect the often directional influence of sea/land processes, which is found to be highly correlated with northing. This may mask the true influence of the fall in available radiant energy owing to the earth's curvature that is represented within the northing variable. That the influence of urbanisation is felt more strongly for minimum temperatures than maxima is anticipated from the literature (Oke, 1987, p290). Cooling during the evening is slower within urban areas, resulting in higher nocturnal temperatures than those expected in rural locations.

Strong differences according to direction materialise amongst the variables selected when modelling minima. South coastal influences, for example, are more likely to be associated with anti-cyclonic conditions owing to the south/south-westerly bias in the direction from which these systems are likely to be travelling (Figure 4-2 (b)). The relatively large land-sea temperature differences of the east coast as opposed to those of the Gulf stream to the west make the greater influence of indices based on eastings unsurprising. Under conditions of low vorticity, this directional bias is however less apparent as indicated by the increase in selection of land/sea ratio (pcoast25) under situations of low pronounced vorticity. The impact of coastal influence at any one location is likely to depend on relative land-sea temperatures and the strength and direction of the prevailing wind. This means that any relationships are likely to be highly variable, and non-linear with distance from the coast.

Landscape wide shelter (hightsouth, hightwest, highsouth, highwest) showed variable correlations with both maximum and minimum temperatures. High degrees of shelter may give rise to different effects according to the weather type prevailing. In general, minimum temperatures in sheltered areas are expected to be lower since cold air has more opportunity to lie within local dips, while mixing in exposed areas makes this less likely. This is the consistent pattern seen for hwest. The variable incorporating an element of north-south barrier (hightwest) in contrast shows more variable correlations, suggesting that this may on occasion be accounting for föhn type effects with warming of the air on the lee side of the barrier, as intended. Limiting the distance over which such effects occur might serve to further improve the explanatory power of this variable.

Terrain shape is known to have a considerable bearing on minimum temperatures in particular (Tabony 1985). The increase in minimum temperatures with increased local roughness may be attributed to improved mixing within the atmosphere which prevents cold air ponding in local pockets, especially given the occurrence of this relationship under mixed and low pressure weather systems. At a smaller scale however, the lower minima associated with larger standard deviations in height over a broad ($50km^2$) area (stdev25) may be attributable to increased exposure within upland areas. Less straightforward to interpret in isolation are the results indicating the ability of variables such as down10, htmedlar to account for cold air ponding under anticyclonic weather systems, as intended. Computation of lapse rate on a day by day basis *without* including these additional factors however suggests the unlikely situation of positive lapse rates for the whole of England and Wales under anticyclonic conditions (Appendix 9). Their inclusion was therefore found to improve the overall estimation of minimum temperatures.

Interestingly, it is the variable drop10 rather than heights above the various sizes of watershed minima (e.g. htlarge, htmid) that provides the anticipated positive relationship between minimum temperature and height above the area minimum that is expected from an understanding of katabatic process and the resultant ponding of cold air within hollows and basin bottoms. Katabatic flow usually occurs over a 20km maximum distance, or less. While the basins represented by htmed and htmedlar fall within this size range on average, it may be that in general the basins delineated are too large. Additionally, cold air is unlikely to reach up the steeper slopes towards the sides of a valley, so the linear relationship assumed within the regression modelling may only be appropriate for a limited distance above the valley base if at all. The lack of strong relationship for local topographic effects and local minima encountered may also arise because the variables developed did not incorporate a measure of the area over which cold air may collect in upland plateau areas and of obstacles to downwards flow such as upland forests. However, the volume of flow accumulation used in constructing the watershed-based variables (p99) was adjusted according to elevation in order to account for the greater coldness of air from upper reaches. As Manley (1944) notes, '*Much depends in the characteristics of the valley and its trend, whether it has a sizeable stream at the bottom, whether it is wooded, and whether it is narrow and winding or broad and open*'. While the presence of rivers and measures of concavity were included within the analysis, the manner in which these factors interrelate is clearly complex and potentially beyond the capabilities of the linear modelling used in this (and similar) studies. Compound representations of terrain shape, such as the principal component derived classifications of local terrain used within the Aurely approach for rainfall (Mestre 1997) or multi-scale wavelet transformations of terrain (e.g. Gallant and Hutchinson, 1996) might prove more successful in encapsulating the forms of valleys more prone to cold air ponding. Additionally it is likely that the conjunction between the accumulation of cold air with other processes such as the influence of the sea, which combine for example at the base of many larger valleys, does not occur in linear fashion. In contrast, the local basin feature (htbasin) proves more effective than drop4 within local basin areas with the expected positive relationship. This suggests non-linearity in the depth of cold air with height above the valley. A small basin is more likely to be fully filled with cold air than a larger, flatter based basin.

It is also worthwhile to consider some variables where a relationship was hypothesised for which no marked relationship, either in strength or consistency of selection, was found. Measures relating to aspect and gradient fall within this category. This is attributed to two main factors. Firstly, the resolution at which the variables are derived (1km^2) means that only large scale changes in slope will be identifiable. Slope and aspect *are* known to affect temperature through differences in solar radiation received (Linacre 1992, p193), but the relatively crude modelling resolution is likely to be masking many of the more local effects that result from terrain shape in small valleys. These findings are consistent with Cornford's (1997) results for winter temperatures computed to a resolution of 500m, indicating the highly localised effect of these processes. Secondly, the standard exposure of UK meteorological stations means that data are preferentially collected from flat, open areas. On both counts, the apparent lack of relationship between temperature and slope and aspect in Figure 4-1 and Figure 4-2 is unsurprising. Work by Bolstad *et al.* (1998) incorporates a previously defined (empirical) correction to account for the relationship between slope and aspect and insect phenology to compensate for this problem. However, such corrections may be local in reliability.

The individual parallel representations of Figure 4-2 reflect the day-to-day variability in the relative strength of relationship between variables and maximum and minimum temperatures. This highlights the importance of adaptability in any interpolation system that models daily temperatures, as opposed to monthly data. Within Figure 4-2 this variation is most apparent as a reflection of different processes occurring by weather type. Less obvious are winter/summer differences, for example in maritime influences that are reflected through the 'bipolar' effects within Figure 4-2 that show temperatures both increasing *and* decreasing with measures of distance to the coast. Coastal areas for example are expected to be warmer than those inland in winter and yet colder in summer.

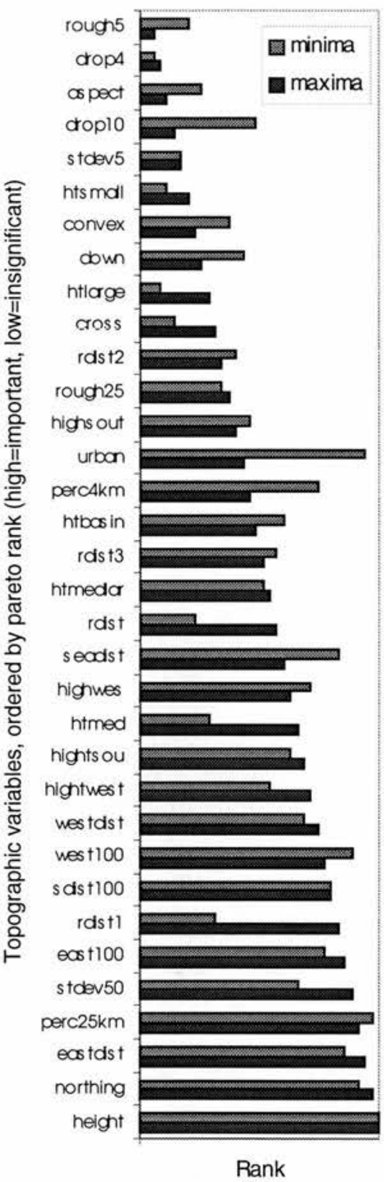


Figure 4-3. Summary Pareto rank (significance and consistency) association of topoclimatic variables with maximum and minimum temperatures, 1986

The measure of direction in addition to strength of relationship portrayed within Figure 4-2 also reveals important patterns of cross-correlation within relationships of which a number of examples have been discussed above. These differences would be masked within summary plots. Overall however, allowing the inclusion of cross-correlated variables within the analysis in order to find the 'best' variable of several that might mimic a particular process or set of processes (e.g. maritime influence) introduces both statistical and interpretation problems within the analysis. For example, the apparent influence of variables representing a certain group of processes is spread over the variety of options (e.g. use of *both* edist, edist100 and similar), such that their combined importance became more difficult to assess. Principal component transformations of the 35 regression variables were explored as a means to combat this issue. However, these proved difficult to interpret in a physical manner since correlations existed not only between variables introduced for the same purpose but also between those representing different issues. Additionally, their use in other studies has similarly showed little practical benefit (Lennon and Turner 1995, Cornford 1997).

The use of automated stepwise regression techniques for this assessment of appropriate guiding variables raises a number of practical and theoretical issues in addition to those of non-linearity, non-normality and cross-correlation within and between the variables raised already. In particular, it assesses the strength of relationship between temperature and individual variables rather than through the selection of strong predictive subsets (SPSS, p184). Automating the choice of regression variables by 'best subset' methods however leads to a choice of 'best predictor' rather than focusing on the strength of explanation achieved using stepwise methods. On a more pragmatic note, the number of possible combinations of 40 variables for any one day and the dependent temperature parameter (maximum or minimum) also exceeds those computable in standard statistics packages such as Minitab or SPSS. This further explains why the theoretical ideal of manually assessing each combination on the basis of small error and high explanatory power is infeasible for a study such as this.

When restricted to using a fixed set of variables as in this case, the requirement for daily adaptability (Figure 4-2) suggests the need to include in the estimating equations both the most consistently selected variables and those only rarely selected but of considerable influence on the days when these are chosen. This will introduce potential redundancies of information. However, the benefit is the added flexibility to better predict temperature conditions occurring under unusual but potentially significant weather conditions (e.g. during strong anti-cyclones). For pests, the steady accumulation of temperature is known to correlate strongly with overall development while the occasional frost may for example prove crucial to survival given their small frames and short lifespans. Figure 4-3 provides a summary comparison of variables influential to maximum and minimum temperature in order of their combined 'pareto' rank, the pareto method signifying the compromise solution between variables that are occasionally quite influential versus those that are consistently selected. The influence of urban areas is found to be important for predicting daily minima but not influential in the case of maxima. The effect of directional coastal influences is less pronounced for minima than maxima. The pareto technique also allows the influence of the standard deviation in height (stdev25) to the identified, otherwise unclear from Figure 4-1 and Figure 4-2 alone owing to its consistent, 'low-grade' selection.

Figure 4-3 summarises the discussion of significant topoclimatic and land cover factors affecting maximum and minimum temperatures. However, these ranked variables provide several cross-correlated alternatives for any one particular purpose, since various options were chosen through the automatic procedures on different days. Collinearity is known to create ill-conditioned matrices where small changes in the data values may lead to large differences in the estimates of the coefficients, such that restricting the variable set further is an important next step within the analysis. Additionally, the effect of the way in which different variables are ranked has yet to be explored. By limiting the major variables listed (Table 4-1) to those with partial inter-correlations of absolute value 0.5 or less, a subset of variables was obtained for both maximum and minimum temperatures using the pareto ranking method (Table 4-2).

Table 4-1. Top 15 covariates, maximum and minimum temperature

	Maximum	Minimum
1	height	height
2	northing	pcoast25
3	edist	urb
4	pcoast25	northing
5	stdev50	wdist100
6	east100	edist
7	rdist1	seadist
8	sdist100	sdist100
9	west100	edist100
10	westdist	pcoast4
11	htwest	highwest
12	hsouth	wdist
13	htmed	stdev50
14	hwest	htsouth
15	seadist	htbasin

Table 4-2. Covariates to be used in the interpolation of minimum temperatures

(-0.5 < Partial correlation coefficient > 0.5)

	Maximum	Minimum
1	height	height
2	northing	pcoast25
3	pcoast25	urb
4	stdev50	northing
5	edist100	wdist100
6	rdist1	seadist
7	sdist100	sdist100
8	wdist100	edist100
9	wdist	hwest
10	htwest	wdist
11	hsouth	stdev50
12	htmed	htsouth

Perhaps unsurprisingly, reflecting the strong maritime influence over British climate, multiple measures of distance to the coast are reflected within the pareto ranks in all major directions in addition to the non-directional land/sea ratio (pcoast25). For minimum temperatures, the urban index finds a strong position within the pareto rank owing to its consistent selection, but albeit weak strength of relationship. The dominance of northing is much lower in the case of minima than maxima, especially in terms of strength of relationship.

4.1.2 Sensitivity of interpolation techniques to their model parameters

The sensitivity of individual interpolation techniques to their mathematical parameters has been the subject of much previous discussion within the literature. Using the 'best' set of guiding variables chosen from the last section, the sensitivity of the techniques used within the study and in particular the performance of automatic parameter derivation techniques when interpolating daily maximum and minimum temperatures is explored in this part of the chapter.

4.1.2.1 Trend surface

Trend surface interpolation in this work is taken to include additional linear guiding covariates in addition to the 'trend' form. Specifying the order of the trend itself is an important component of the interpolation process. Figure 4-4 below illustrates the relationship between the form of the trend and the daily r.m.s. error aggregated to provide an annual average interpolation accuracy for orders of trend between 2 and 4.

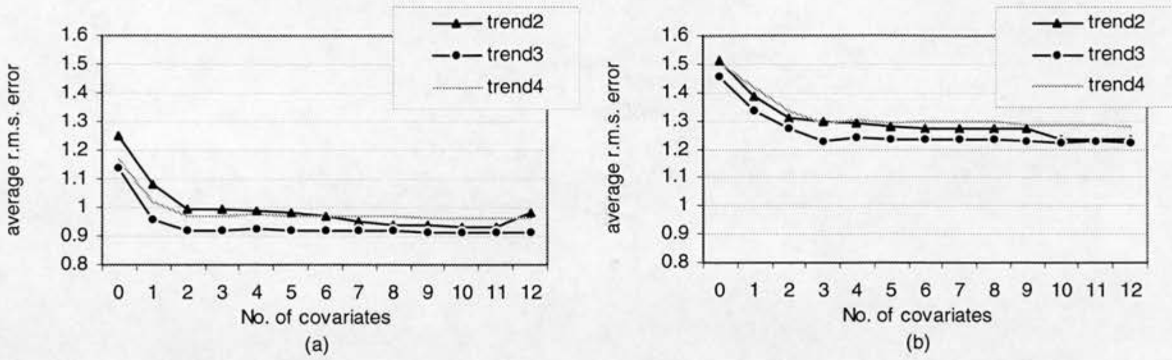


Figure 4-4. Effect of the order of trend surface on annual average daily r.m.s. accuracy for (a) maximum and (b) minimum daily temperatures, 1976

For maximum temperatures in particular (Figure 4-4(a)), considerable improvement in interpolation accuracy is gained by increasing the order of the trend to 3. However, for both minimum and maximum temperatures, trends of order 4 perform worse than those of order 3. This suggests that the third order model is the optimal degree for interpolating temperatures using this national data set. Given the likelihood that minimum temperatures are more variable than maxima, it is however surprising to see less improvement in the case of minimum temperatures when increasing the order of the trend than for maxima.

4.1.2.2 Partial thin plate splines

Unlike the spline models commonly facilitated within proprietary GIS, the partial thin plate spline model implemented within this study allows the automatic construction of interpolation covariance matrices through use of generalised cross-validation (p113). In principle, this should provide more appropriate estimates of the smoothing and tension parameters than by their ad-hoc specification or estimation. Confirmation that these automatic procedures produce equations that fall within acceptable mathematical bounds should nevertheless be an important component of any study. This is particularly the case within this chapter, since partial thin plate splines have rarely been used to interpolate *daily* maximum and minimum temperatures previously, especially over such an extensive area. It is possible that the technique will over smooth the results, for minimum temperatures in particular. Diagnostic trace parameters are therefore reported over the full annual cycle of 1976.

The automatic selection of parameters using the GCV does not adjust for alternative degrees of spline model in addition to smoothing parameters, however. The results of exploring both second and third order splines are therefore also reported, as are splines that incorporate elevation as an adaptive, independent spline variable rather than a linear (partial) covariate (Table 3-9).

Trace diagnostics

As Hutchinson (In Press) demonstrated, the value of the 'trace' from the spline model provides a diagnostic measures of overall interpolation model performance. Figure 4-5 illustrates the variability of model trace (Figure 3-16) for maximum (Figure 4-5(a)) and minimum (Figure 4-5(b)) temperatures throughout 1976. Considerable variability may be identified on a day-to-day basis, and the acceptable limits for trace values given the number of data points, order of the spline and number of covariates are shown using cross bars as a guide. For both maximum and minimum temperatures, the basic spline result without any added guided variables (trace 0) is compared with those using 9 variables in the case for minima, and 5 for maxima. In the case of maximum temperatures 76% of days in the year were found to be within range, while for minima this percentage rose to 85%. This may come as a surprise when considering the hypothesised smoothing nature of the splines and the statistically better covariate models obtained for maximum temperatures. Without added covariates, an acceptable model was parameterised for maxima on only 33% of the days in comparison with 73% for minima. On this evidence, the idea that splines without covariates can adequately model the large-scale trend in maximum temperatures can be rejected.

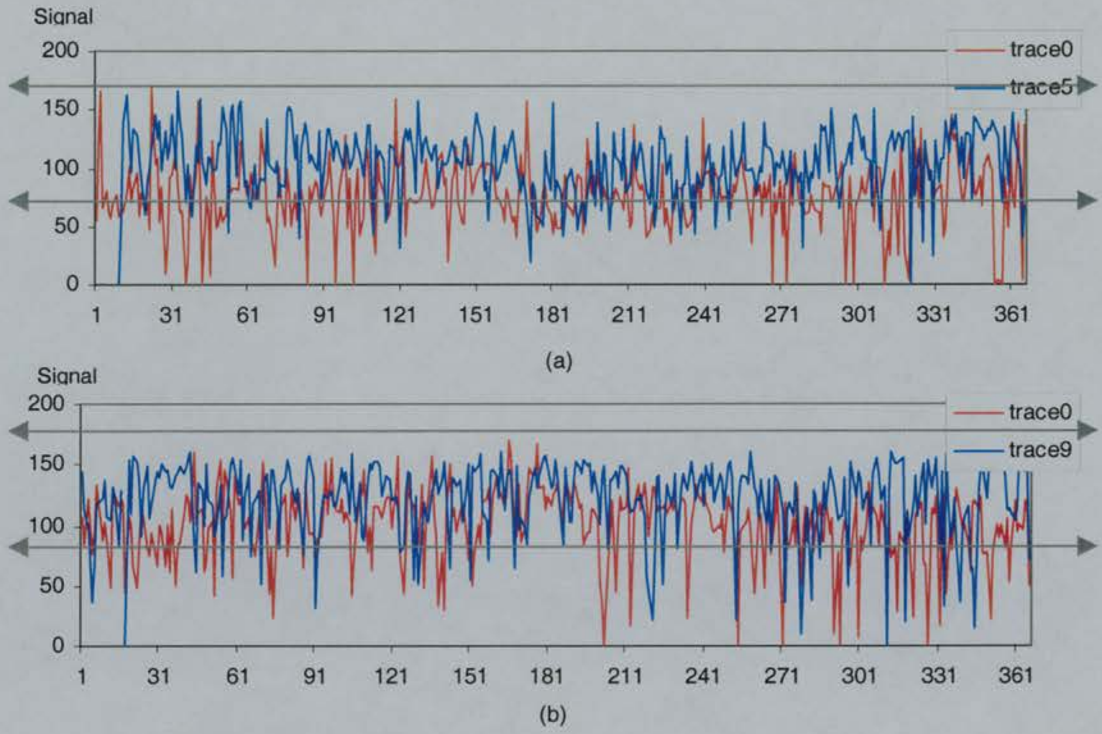


Figure 4-5. Variability of 'trace' from spline model for (a) maximum and (b) minimum temperatures, 1976, by number of guiding covariates (Signal of partial thin plate spline model as per p115)

Order of the spline

The effect of altering the order of the spline is summarised within Figure 4-6 below, which indicates the accuracy statistics for splines of between second and fourth order. Increasing the order of spline worsens accuracies for maximum temperatures more than minima, increasing the average daily r.m.s. error by up to 0.4 (40% of the 'best' estimate). The results confirm the use of 'standard' 2nd order splines for interpolating both maximum and minimum daily temperatures, with further improvements best obtained through the incorporation of additional linear covariates.

The success of elevation as a third independent (as opposed to dependent, partial) variable may depend on the relative scale used to measure height in relation to distance as Hutchinson (1998) demonstrates with regard to daily Alpine rainfall. For this study however, altering the elevation/distance ratio made little improvement. Spline models using two independent variables only remained preferable. This is perhaps surprising given that one of the few published accounts of partial thin plate splines being used to interpolate daily minimum temperatures (Laughlin *et al.* 1993) use elevation as an adaptive third independent variable in order to reflect locally extreme minima within frost hollows. The result may be attributed to a lack of data points in *both* the bottom and top of significant valleys. Just as co-kriging performs poorly in cases where the relationship with the third variable is predominantly linear and the data are sparsely located (e.g. Collins *et al.* 1996), so is it the case here with the spline model that uses elevation as a third independent variable.

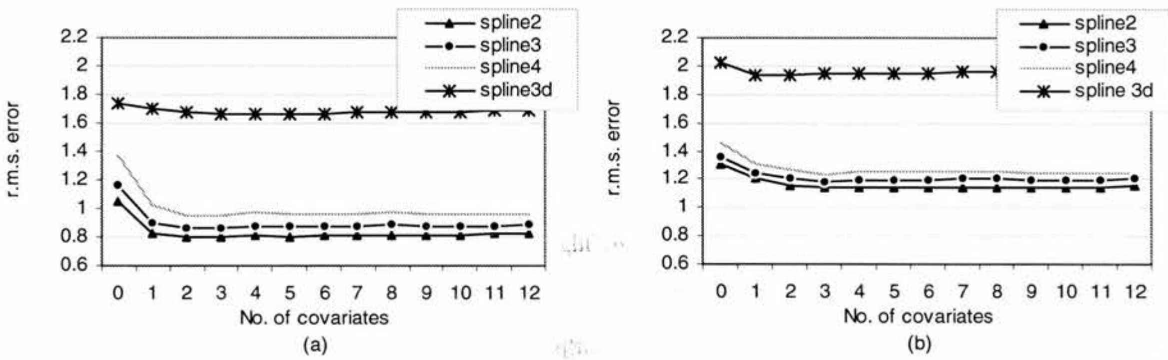


Figure 4-6. Effect of the order of the spline on the annual aggregate r.m.s. accuracy for (a) maximum and (b) minimum daily temperatures

4.1.2.3 De-trended inverse distance weighting

In the case of inverse distance weighted interpolation, two parameters affect the accuracy of interpolation. Of major importance is the power parameter, selected in this study by the Levenberg-Marquandt method. As with spline trace diagnostics and variogram modelling, checking the realism of this automatic process is an important component of analysis. In conjunction with the power parameter, the neighbourhood within which data are searched (number of contributing points) is thought to play a less critical role but is investigated for clarity.

Power parameter

Given that the potential values of the power function are unbounded from a mathematical perspective when using the Levenberg-Marquandt fitting process, a maximum power of 10 was used to constrain the interpolation system. As the 'spikes' within Figure 4-7 show, this default was necessary only for a minority of days in the year (approx. 4-5 for both maximum and minimum temperatures) when little spatial autocorrelation (or unrepresented trend) was present in the data. On average, the power parameter for maximum temperatures was estimated at 1.77 and 1.99 for minima. This higher power function for minimum temperature is expected given the greater spatial variability over local distance of that variable. The higher power effectively increases the distance decay effect and places more weight on nearby, as opposed to distant, meteorological stations.

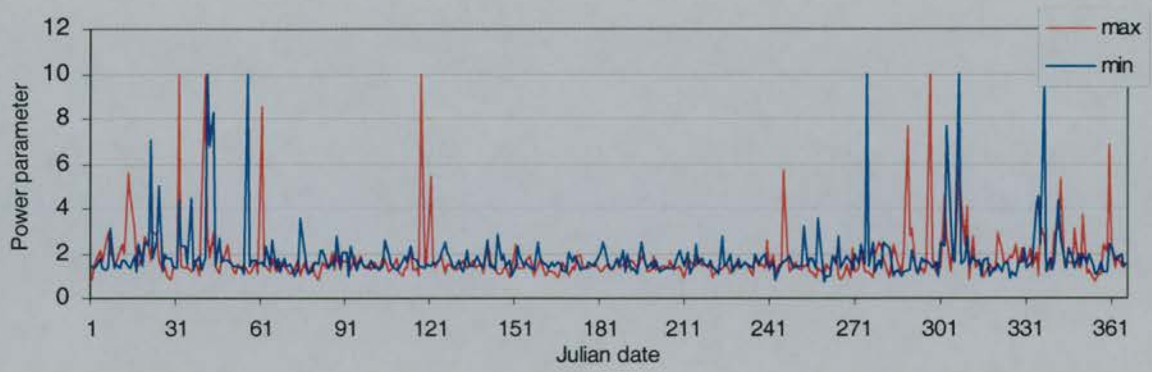


Figure 4-7. Estimated power parameters, daily maximum and minimum temperatures 1976

Search neighbourhood (number of stations)

Alterations to the search neighbourhood were less influential on the aggregate annual accuracy for both maximum and minimum temperatures than the power parameter. For maxima, a standard 12-point neighbourhood provided a slight improvement over both increasing and decreasing the search space may be interpreted as a function of the aggregate nature of the results. Decreasing the search space to 6 points has a greater influence than increasing its value, since on days where the power function is high but the radius large, distant points that are included erroneously should have relatively little influence on the result. Conversely, where the power function is low but the search neighbourhood small the greater influence of search space may be seen.

4.1.2.4 De-trended ordinary kriging

As when computing the power parameter each day for inverse distance weighting, the computational overhead associated with computing daily variograms automatically is considerable. Following visual inspection of datasets for nine days of differing weather type and season, the exponential model was selected for sole use in the automatic analyses to minimise the number of possible options. This choice of exponential function concurs with that of Cornford (1997). Using a similar temperature data set for England and Wales, Landau and Barnett (1996) however opted for the less sensitive power function which more closely resembles the procedure used when fitting the inverse distance weighting power above.

The average nugget variance for maximum temperatures modelled automatically was 0.195°, while for minima this rose to 0.3°. The nugget for minimum temperatures was considerably more variable, with a standard deviation of 0.42° in comparison with that for maxima at 0.19°. Taking the interpretation of nugget variance as measurement error in the underlying temperatures, these values appear a reasonable approximation for climate recording instruments. There is however no particular rationale for the error when measuring maximum temperatures to be lower than for minima, and the higher average nugget variance for minima may additionally reflect higher micro-climatic influences.

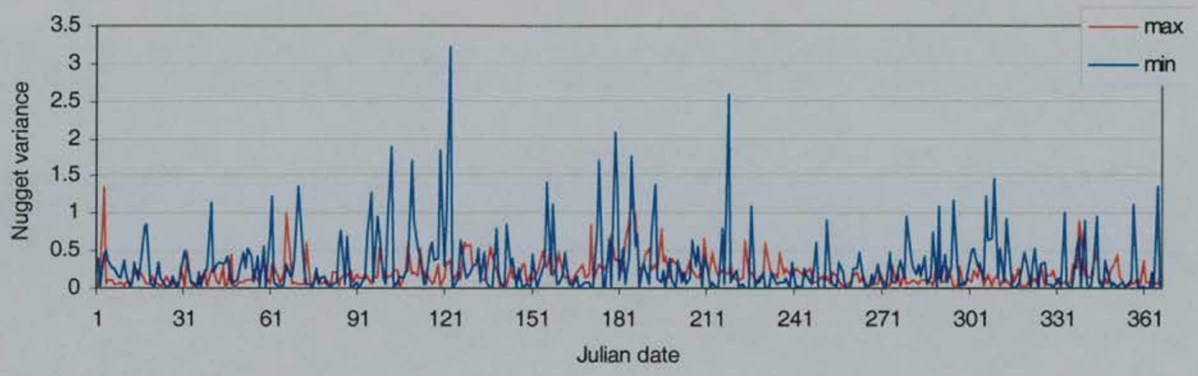


Figure 4-8. Nugget variance of the automatically modelled (exponential) variogram for maximum and minimum temperatures

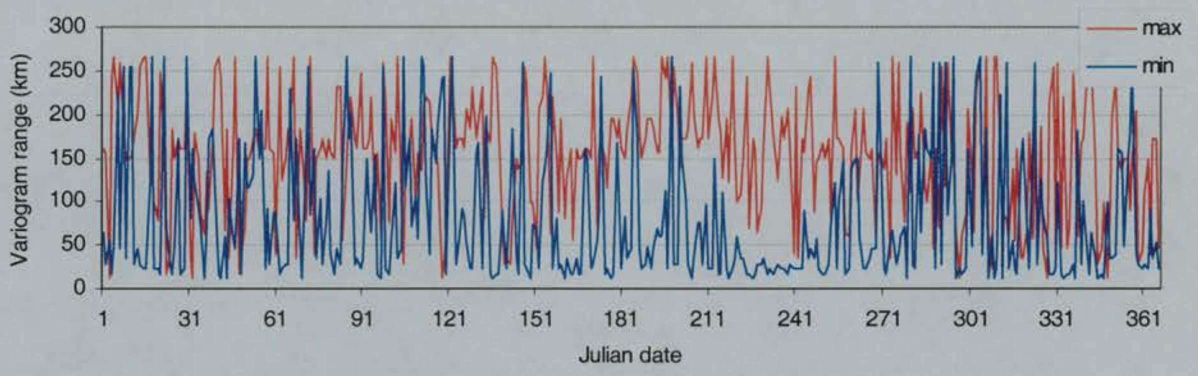


Figure 4-9. Range of the automatically modelled (exponential) variogram for maximum and minimum temperatures

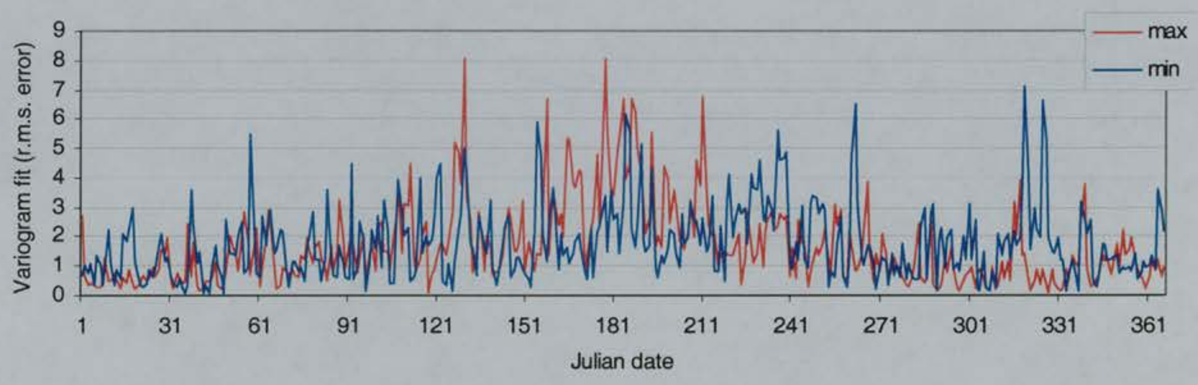


Figure 4-10. Effectiveness of fit of the automatically modelled (exponential) variogram for maximum and minimum temperatures

Variations of the variogram range, both for maxima and minima, are considerable. As identified within Figure 4-9, the average range for minimum temperatures (82km) is much shorter than for maxima (154km) and has a slightly higher standard deviation throughout the year. In terms of modal distribution however, the modal average range for maxima is 172km and yet only 22km for minima. 22km was the default minimum range in the event of fitting problems, suggesting that problems fitting an appropriate variogram on a proportion of dates are occurring for minimum temperatures in particular. This was confirmed with problems of matrix instability on a number of dates when using the Levenberg-Marquandt gradient descent algorithm as a more computationally efficient variogram modelling approach. Iterative fitting is rather more graceful in its treatment of variograms for which no spatial autocorrelation is apparent, and without recourse to Figure 4-10 can imply feasible (but inaccurate) results. Comparison between Figure 4-8 and Figure 4-10 show the days of higher nugget variance are also a good indicator of days where model fit is weak.

Assessing the accuracy of fit achieved is somewhat subjective since visual interpretation forms the means of comparison. Values for nugget and range for nine dates of differing weather type and season were assessed visually using *Variowin* (Pannatier 1996) and were found to be reasonable approximations. The volume of data available for variogram modelling (174 sample points) was however low given the national extent of the study, and it is likely that additional short lag data would assist in improving the results for minimum temperatures in particular. Reliance on a fixed network of recordings makes such sampling recommendations difficult to achieve, as discussed within chapter 3 (p84).

The effect of modelling bi-directional variograms was explored using the prevailing wind direction for Britain (south-westerly) as the major axis, in comparison with the orthogonal north-easterly direction. The effect of modelling anisotropy along this fixed south-westerly/north-easterly axis proved (marginally) detrimental to the aggregate results for both maximum and minimum temperatures. More adaptive measures for modelling anisotropy, with direction variant according to daily weather pattern, are suggested following the visual exploration of variogram 'surfaces' for nine days of varying weather pattern and season. Levels of anisotropy were found to vary markedly despite the extraction of major trends from the data, both in extent and direction, such that the SW/NW axis was not necessarily the most suitable for any one particular day.

Automatic fitting is only justifiable where the variability of the underlying data demands it, and the accuracy of fit achieved is acceptable. Both Figure 4-8 and Figure 4-9 indicate strong variability in both nugget variance and model range respectively. The better that the underlying process is modelled, arguably the lower these daily fluctuations should be, and from this perspective the results are somewhat disappointing. The use of one 'annual' covariate set for the whole year rather than adaptive sets under different weather types might serve to reduce this variability. However, separating the nature of trend and semivariance, as noted within Section 3.3.2 (p110), is an art rather than absolute science. This is a theme that will be returned to within the discussion at the end of the chapter.

4.1.3 Quantitative comparison between interpolation methods

4.1.3.1 Sensitivity of interpolation techniques to the incorporation of guiding covariates

The pay-off between adding further covariates versus the use of more complex interpolation techniques has received little attention within the literature. Cornford (1997) for example suggests that attention to guiding covariates is more crucial than considering statistical differences between mathematical interpolators. Mitás and Mitásová (1999) concur with this view in their suggestion that research possibilities lie more with the incorporation of process than with the development of increasingly complex statistical interpolation theory. This section reports results showing the relative improvement of standard interpolation techniques with additional covariates *known* to be significant from the analyses of Section 4.1.1 above.

The working hypothesis for this chapter suggests that making best use of spatial autocorrelation to predict temperatures may be a more efficient way of increasing interpolation accuracies than paying increasingly detailed attention to the selection of guiding covariates. Sophisticated interpolators such as kriging should be able to use the power of auto-correlation to compensate for a lack of knowledge of localised processes as long as major trends in the data have been removed. This should not however be interpreted to suggest that the improved incorporation of process has little theoretical validity, but rather that taking advantage of spatial autocorrelation may be more desirable pragmatically that relying on increasingly complex but mathematically crude linear additive modelling.

Accuracies of the interpolated daily maximum and minimum temperatures, by number of guiding variables and according to interpolation technique, are illustrated in Figure 4-11 and Figure 4-12. The results summarise the daily r.m.s values and the variability of the residual errors using their standard deviation, aggregated to provide annual averages. The guiding variables incorporated within the analyses follow those determined by the 'compromise' selection technique of Section 4.1.1. The benefits of additional covariates are minimal for maximum temperatures Figure 4-11(a)) and indeed appear to *increase* marginally the average standard deviation of the daily residuals (Figure 4-12(a)). For minimum temperatures, additional covariates reduce both the average daily r.m.s. errors and the average standard deviation of the residuals with the inclusion of up to 9 guiding variables when taking both standard deviation in addition to r.m.s error into account, but the majority of improvements are realised after just three. Relative to the figures for trend surface analysis, partial thin plate splines for minima perform considerably better in terms of r.m.s. error (approx. 0.25°C improvement with one covariate) and its annual standard deviation (approx. 1/3 lower for one covariate) with fewer guiding variables. This may be attributed to the intrinsic capability of the partial thin plate spline method in comparison to the less flexible and pre-determined form of the trend surface. With an increased number of covariates however, the differences between techniques become relatively slight.

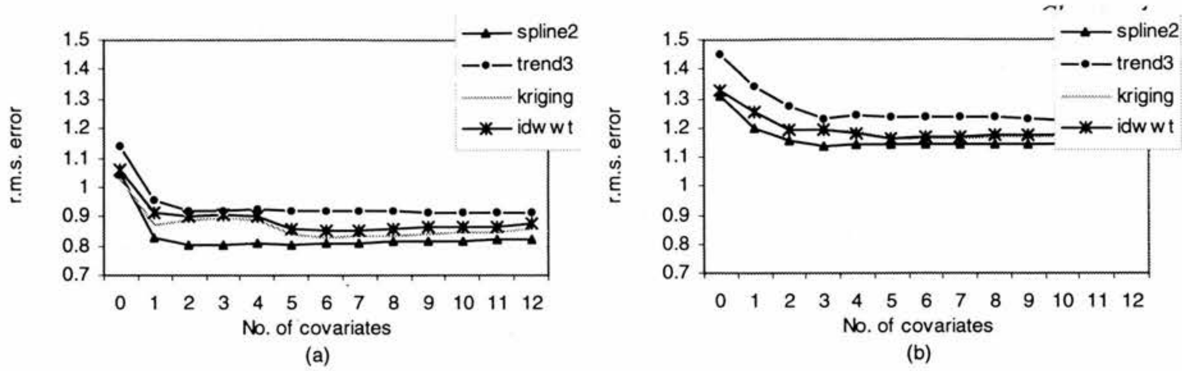


Figure 4-11. Annual average r.m.s. error by interpolation method and number of covariates of (a) maximum and (b) minimum daily temperatures, 1976

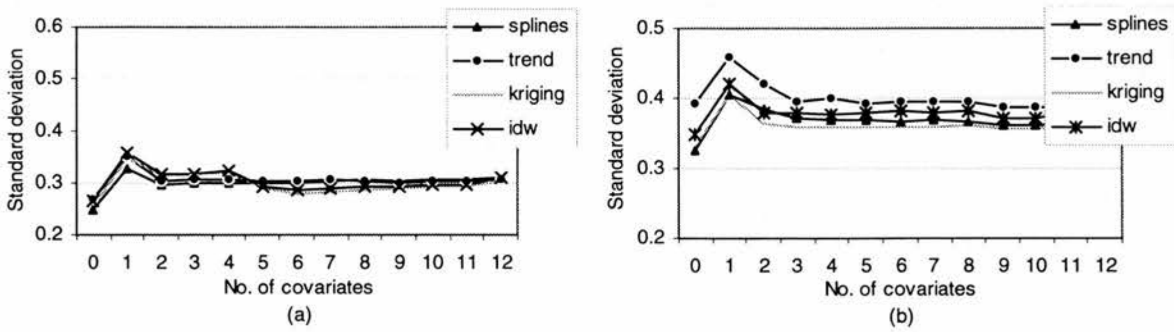


Figure 4-12. Annual standard deviation in average r.m.s. error by interpolation method and number of covariates of (a) maximum and (b) minimum daily temperatures, 1976

Compared with the two global methods reported above, aggregate r.m.s. accuracy and standard deviation results for inverse distance weighted interpolation fall between the two techniques reported so far. The benefit of additional covariates becomes negligible after 6 variables in the case of maximum (Figure 4-11(a)) and minimum temperatures (Figure 4-11(b)) with profiles less steep than those for trend surface interpolation. Comparisons between de-trended ordinary kriging as the more sophisticated local interpolator and automated inverse distance weighting for both maximum and minimum temperatures show surprisingly small differences in r.m.s. error.

Overall, the results Figure 4-11 and Figure 4-12 indicate that the rewards to be gained by incorporating increasing numbers of guiding variables are diminishingly small. This may in part relate to the problems associated with multiple linear regression and daily variability in the most appropriate gridded variables required.

Within this study, day-to-day adaptability within the interpolation process was achieved by varying the strength of regression coefficients in the trend model from day to day. The actual set of variables used however remained fixed throughout the year. This was because the complexities of data management, where both daily maximum and minimum temperatures for annual (or longer) sequences are interpolated, in translating such classifications to a complex regression system involving different dummy variables per day and per variable would be considerable. Inevitably, this is likely to mean that the variable set is, in general, over specified with redundancies in relationship occurring in a regular basis. Arguably, greatest attention should be paid in the selection of the guiding variable set to the most common weather type occurring over Britain throughout the year in order to minimise overall average error. The simplified Lamb classification provided a useful measure of prevailing weather system for the analyses of Section 4.1.1, although its manual (and subjective) nature mean that it will not be an appropriate choice of classifier for real-time pest forecasting where automatic procedures would be required. Improving the categorisation of weather pattern further, and accounting for the differing effects of frontal systems by using local rather than global regression, are similarly potential improvements but whose implementation in the context of this thesis where the emphasis is on pest risk assessment was not feasible. Such measures might minimise collinearity, and maximise the effect of individual variables when chosen.

Studies such as Cornford's (1997) which focus exclusively on their construction may 'over engineer' the resultant model. This is particularly the case for the more mathematically sophisticated automated algorithms (partial thin plate splines and ordinary kriging). In the cases of ordinary kriging and inverse distance weighting, it appears that invoking local spatial autocorrelation can indeed compensate for a lack of specificity regarding process. For partial thin plate splines, which adaptively model the global variability of the surface, similar conclusions may be drawn. Ordering the interpolation techniques according to their overall sophistication and flexibility (trend surface, IDW, splines, kriging), the number of guiding variables to produce the 'best' result in terms of r.m.s. error and its standard deviation throughout the year form a similar sequence. Defining the difference between trend and local variability is however a matter of some debate even among kriging circles.

Theoretical differences between local and global interpolators raise a further issue when comparing guiding covariates. When kriging, it is critical to eliminate trend in order to model the variogram adequately. This is particularly important when using automatic techniques, as in this case. The deliberate incorporation of variables such as northing and eastdist is therefore critical. For global techniques such as partial thin plate splines and trend surface analysis however, positional co-ordinates form an intrinsic component of the interpolated estimate. To re-specify northing and eastdist as guiding variables therefore introduced an element of redundancy.

4.1.3.2 Annual average error, by interpolation technique

ANOVA analysis on the results of suggested that the choice of interpolator has a significant effect on resultant accuracies, but that the incorporation of additional covariates plays a larger contribution than interpolation method alone in minimising error. However, Figure 4-11 and Figure 4-12 indicate that the differences between all interpolation techniques become small once an appropriate numbers of covariates are included. This number will generally be greater for the simpler interpolation techniques.

Hutchinson (1991b) has suggested that, in general, '*the only serious competitor to thin plate splines is the method of kriging*'. Figure 4-13 suggests that while kriging performs strongly in this case study interpolating daily maximum and minimum temperatures, accuracies using automatic inverse distance weighting are competitive. Overall, partial thin plate spline methods with two to three independent covariates show the best performance for interpolating both maximum and minimum temperatures in the case of this data set (174 points) for England and Wales. T-tests reveal the performance of the 'best' spline model to be significantly better than that of kriging, with greater than 95% confidence.

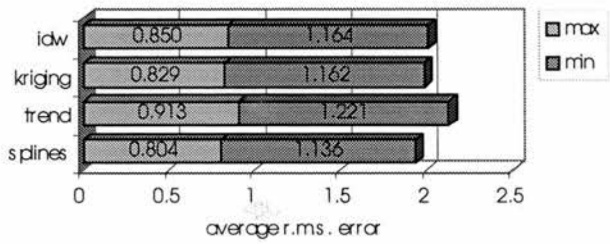


Figure 4-13. Best average annual r.m.s. error by interpolation method of (a) maximum and (b) minimum daily temperatures, 1976

That kriging does not outperform splines, as the limited literature comparing these techniques suggests it should when interpolating irregular data (Laslett 1994), may reflect the difficulties encountered when modelling the variogram automatically. While kriging has a number of theoretical advantages over the other methods, variogram modelling is known to be a particular shortcoming in realising these gains in practice. Additionally, while Laslett's result is widely cited, it nevertheless relates to a single data set and as such the findings should perhaps be reported as those of particular case study than as a benchmark position. However, difficulties have also been reported (Section 4.1.2.4) in accounting for changes in direction of anisotropy without more sophisticated automatic variogram fitting. Kriging's management of anisotropy is a particularly strong point in its favour. It is conjectured that this overall result could alter towards supporting kriging more strongly should improvements be made to the variogram modelling procedure that allow the kriging process to reflect spatial symmetries better.

4.1.3.3 Mathematical distribution of residuals, by interpolation technique

Figure 4-14 to Figure 4-16 demonstrate the overall distribution in residuals (actual-estimated temperature) for three example dates in 1976, these dates chosen to reflect conditions under predominant different weather patterns according to season. Examination of the plots reveals that there is little bias in the residuals (mean residual approaches zero) taking England and Wales as a whole for each of the four interpolation techniques, for either maximum or minimum temperatures.

For maximum temperatures in particular, residuals for trend surface show the greatest spread and are most likely to be associated with both extreme over and under prediction (Figure 4-14(a), Figure 4-15(a), Figure 4-16(a)). This conforms with the expectation from the literature that global smoothing techniques are associated with extreme predictions. In contrast however, residuals from the more adaptive partial thin plate spline interpolations (also using global smoothing functions) show the greatest tendency to centre towards the mean, which in all cases is approximately zero.

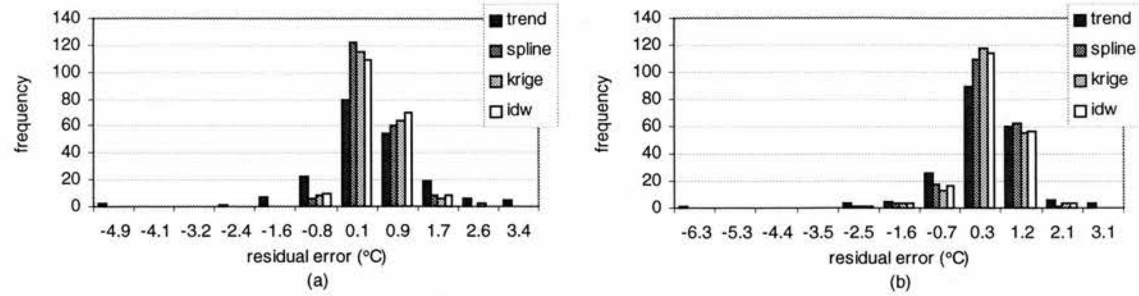


Figure 4-14. Frequency distribution of residuals, 8 January 1976, (a) maximum and (b) minimum temperatures (westerly airflow)

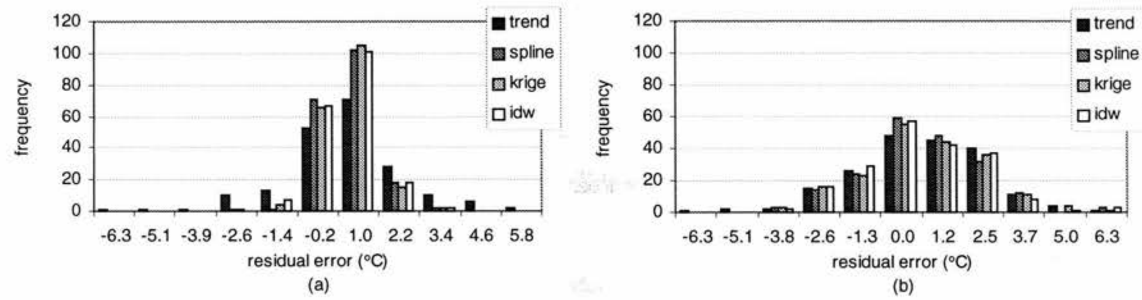


Figure 4-15. Frequency distribution of residuals, 5 September 1976, (a) maximum and (b) minimum temperatures (anti-cyclonic conditions)

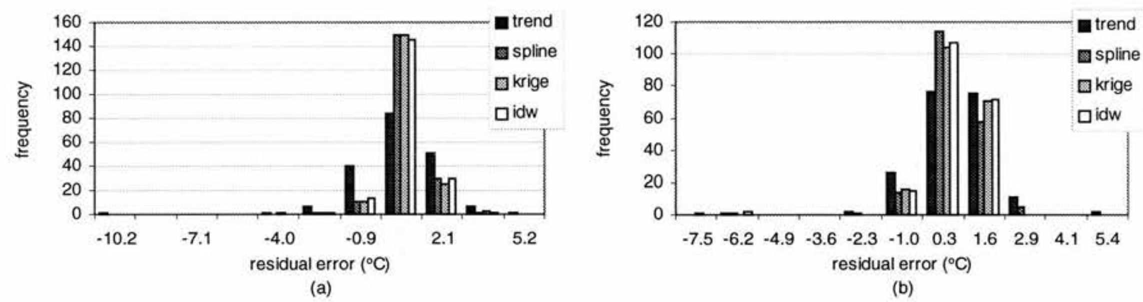


Figure 4-16. Frequency distribution of residuals, 12 May 1976, (a) maximum and (b) minimum temperatures (cyclonic conditions)

Turning to an examination of the residuals from interpolating minimum temperatures (Figure 4-14(b), Figure 4-15(b), Figure 4-16(b)), the overall distribution of errors are for each of the three dates plotted less peaked towards the mean and show higher extremes than those observed for maximum temperatures. This reflects the overall lower average accuracies reported for minimum temperatures (Section 4.1.3.2). Figure 4-15(b) in particular demonstrates that, whatever the method used, difficulties were encountered when interpolating minimum temperatures under anticyclonic conditions. Of the three dates, interpolations proved most suited to approximating both maximum and minimum temperature conditions under westerly air flows (Figure 4-14).

4.1.3.4 Variation in aggregated interpolation results, by date

Daily fluctuations in cross-validated r.m.s. error for maximum temperatures are presented within Figure 4-20 and for minimum temperatures through Figure 4-21. Given that in general interpolation errors might be expected to occur in proportion with the magnitude of underlying values being interpolated, the finding that the absolute r.m.s. errors for maximum temperatures increase and decrease broadly with day length, peaking at the end of June is unsurprising. A plot of r.m.s. error versus daily average temperature over England and Wales (Figure 4-17) confirms this visual assessment. Superimposed on this overall trend however are a number of higher frequency variations. Consideration of Figure 4-17 assists in assessing the relative ability to interpolate temperatures throughout the year. Given the fluctuations in prevailing weather over Britain, a number of these peaks may be attributed to warmer than average weather for the time of year. Julian days 65, 184, 237 and 266 provide examples of this situation. These patterns do not therefore suggest particular problems within the underlying interpolation algorithms.

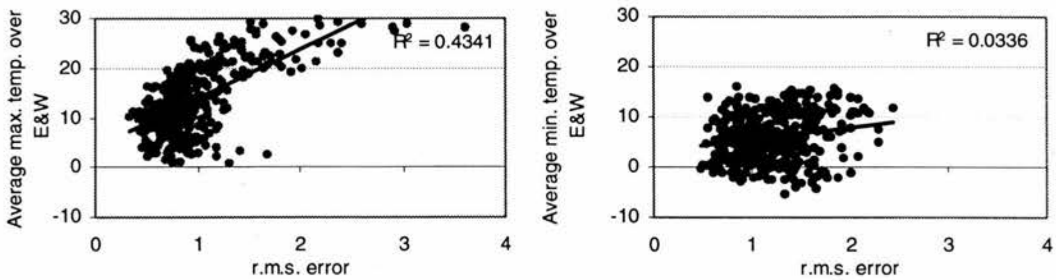


Figure 4-17. Scatterplot showing daily jack-knifed cross-validation error versus average daily maximum and minimum temperatures over England and Wales.

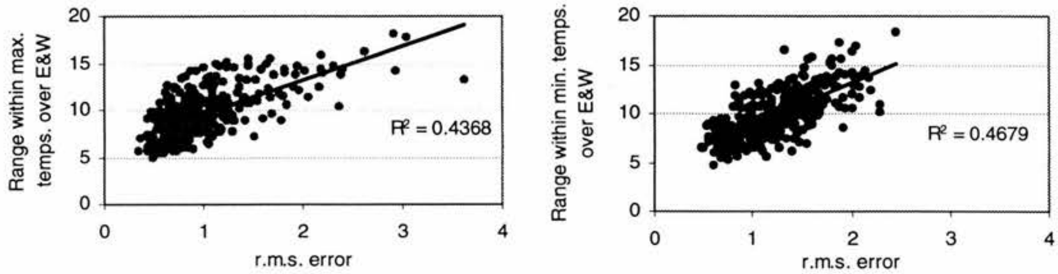


Figure 4-18. Scatterplot showing daily jack-knifed cross-validation error versus range in daily maximum and minimum temperatures over England and Wales

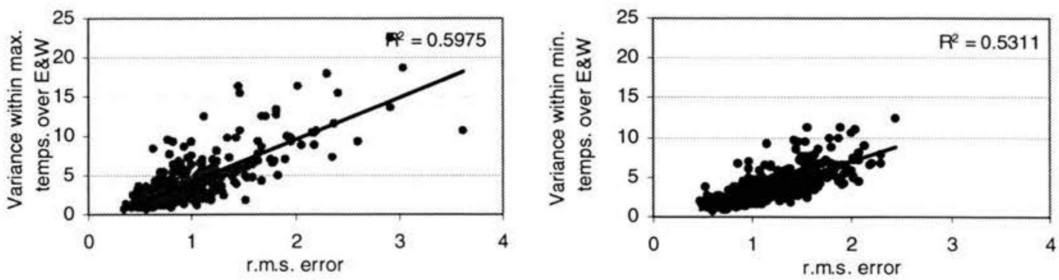


Figure 4-19. Scatterplot showing daily jack-knifed cross-validation error versus variance in daily maximum and minimum temperatures over England and Wales

In contrast, the relationship between r.m.s. error and variance of the underlying temperature data (Figure 4-19, Figure 4-23) in particular are suggestive of difficulties interpolating under particular weather patterns. Peaks in error on Julian days 127, 160, 211 and 338 occur on days of high variability rather than above average temperatures. In the case of maximum temperatures, high variability in the absence of unusually high temperatures is associated with passing fronts, for example under westerly/low pressure systems.

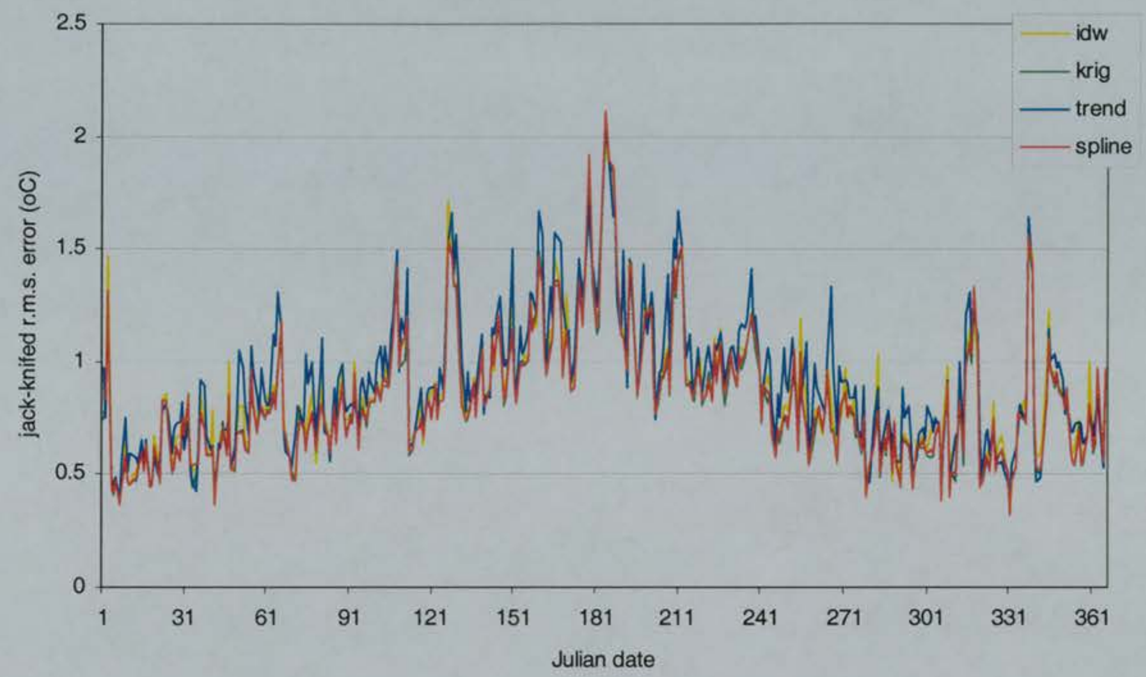


Figure 4-20. Annual variation in r.m.s. error (°C) by interpolation technique, maximum temperatures 1976

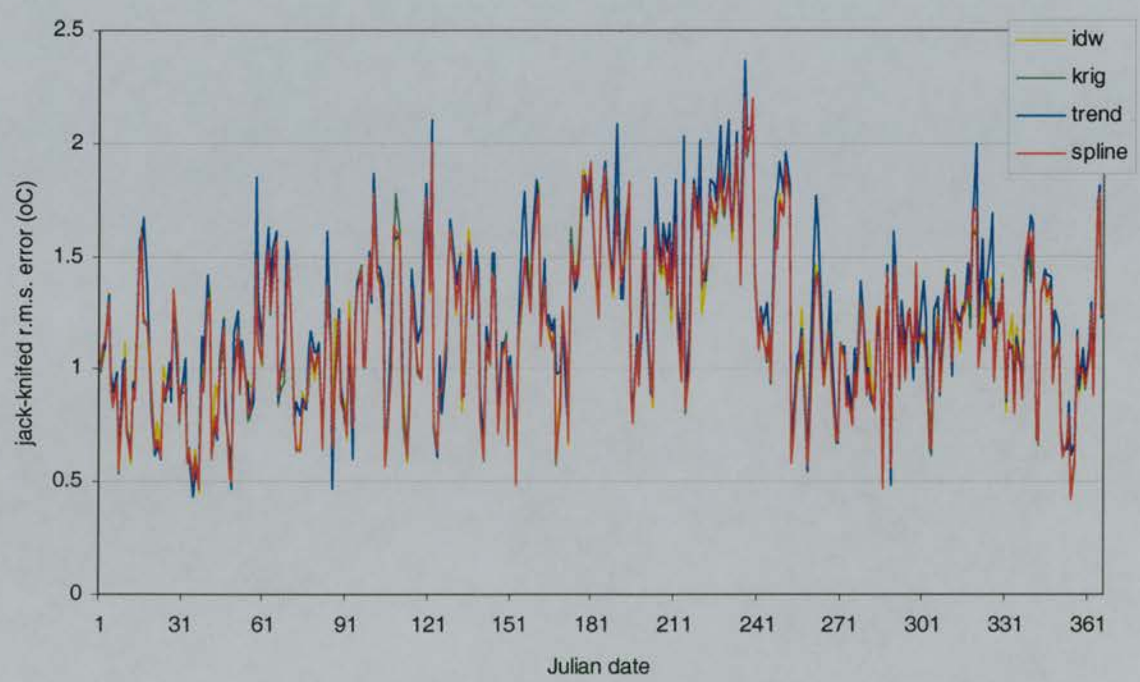


Figure 4-21. Annual variation in r.m.s. error (°C) by interpolation technique, minimum temperatures 1976

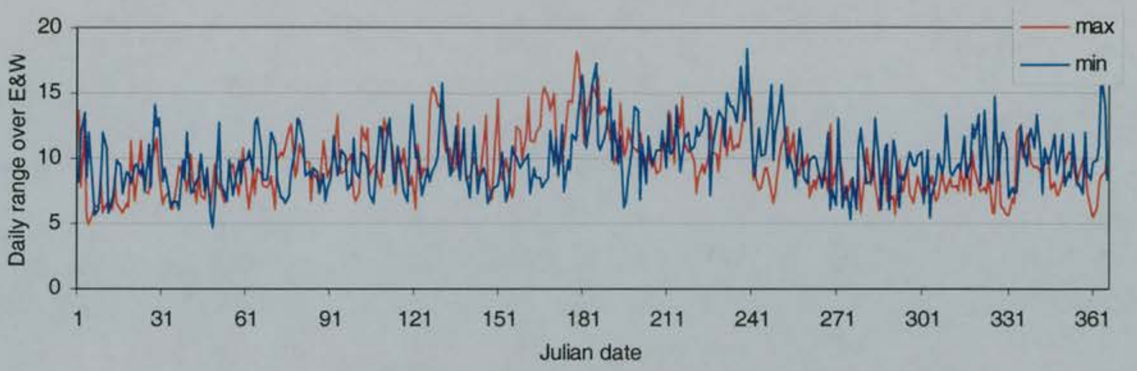


Figure 4-22. Range of maxima and minima over Great Britain, by day, 1976

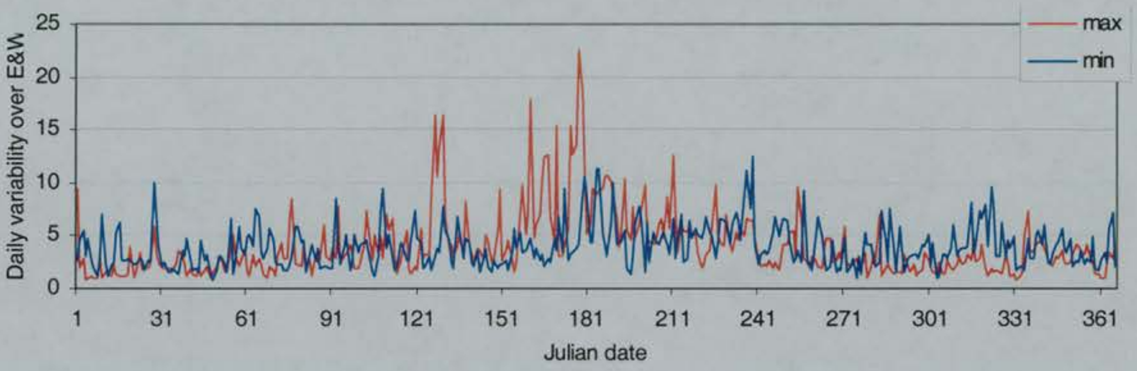


Figure 4-23. Variance of maxima and minima over Great Britain, by day, 1976

For minimum temperatures there is no marked relationship between daily average temperature and r.m.s. error (Figure 4-17). Rather, r.m.s. error relates more strongly to the overall range of temperatures over England and Wales to be interpolated on a particular date (Figure 4-22), and to a greater extent their 'within day' variance throughout the country (Figure 4-23). Range within maximum and minimum temperatures on a particular date are broadly similar in magnitude (Figure 4-22), suggesting that focus be placed on interpreting patterns of weather variability. This confirms that greater scope exists for improvements to the topo-climate and land-cover related indices developed in relation to minimum temperature surfaces within future work, as discussed within Section 4.1.1.3. Analysis using Lamb weather classification records (Appendix 13) shows weather type 0 (anticyclonic, no dominant direction) to be strongly related to days of highest gross error. Cold air flow phenomena, such as katabatic winds, are particularly strong under these circumstances, for which are poorly represented by linear additive modelling. Additionally, the large day/night time temperature differences experienced under clear skies exacerbate the effects of different soils and land cover.

Turning to considerations of the results by technique, partial thin plate splines in comparison with the other techniques are consistent performers on a day-to-day basis. Additionally, they show the lowest aggregate error for maximum and minimum temperatures (Figure 4-13). Figure 4-20 and Figure 4-21 show similar patterns of error by technique, with trend surface interpolation most associated with large 'spikes' in r.m.s. error for both maximum and minimum temperatures. The order of the trend was fixed on the basis of annual aggregate results to a third order function (Section 4.1.2.1), rather than adaptively on a day-by-day basis within the interpolation system as for the other methods. Additionally, it has the least spatial flexibility on a local basis of the techniques. In terms of both aggregate error and management of extremes, trend surface analysis performs poorly. Despite these drawbacks, this has been the preferred method of interpolation within pest phenology systems to date (Régnière 1996, Schaub *et al.* 1995b).

When using 'automatic' inverse distance weighting, larger errors were found for maximum temperatures than minima (Figure 4-20). As local averaging techniques, both inverse distance weighting and kriging might be expected to have similar profiles if these spikes in error for maxima were related solely to extremes within the underlying data. Referring back to Figure 4-7 it seems that these relate to problems defining the overall power parameter on a minority of days. Defining an interpolation function using one as opposed to multiple parameters as in kriging is likely to produce a resultant surface that is less flexible in capturing extreme events. Moreover, kriging weights vary according to the configuration of the data, unlike the distance decay function of inverse distance weighting. The 'averaging' nature of kriging is reflected in the lack of extreme error results for this technique, whose interpolation estimates will tend towards the mean in circumstances of uncertainty (e.g. sparse data).

For minimum temperatures (Figure 4-21), splines similarly are associated with the lowest daily errors on the majority of dates. During the spring however, trend surface results do on occasion outperform the other methods by a considerable margin. This may relate to highly mixed weather patterns over the country, making local association in temperatures highly non-stationary. This must be balanced however against their predominantly strong relationship with the *highest* prediction errors of the four techniques.

4.1.3.5 Summary comparison between interpolation techniques

Differences between partial thin plate splines, ordinary kriging and inverse distance weighting were not significant when automatic parameters were used to condition their form on a daily basis. Varying numbers of guiding variables (the size and direction of parameters for which altered on a daily basis) were however required, according to technique, in order to achieve these comparable results. Trend surfaces however, previously used to construct spatial phenologies, consistently performed poorly.

Partial thin plate splines were selected as the interpolator of choice for both maximum and minimum temperatures for use in the remainder of this work since:

- The best accuracies for both maximum and minimum temperatures, computed on the basis of the annual average of the daily r.m.s. errors in the residuals together with the spatial and temporal variability of the residuals, were achieved using partial thin plate splines;

- Partial thin plate splines were computationally efficient in comparison to the other methods implemented within this study.

4.1.4 Geographical variation in residuals over England and Wales

In addition to investigating the temporal performance of the interpolators throughout the year, assessing the degree to which they follow the predominant spatial patterns in temperature is an important component of a geographical study such as this. Note for example that the use of r.m.s. errors or average daily residual (bias) collapse the geographical representation of the results down to one value, such that localised misfitting may be obscured. This discussion seeks to provide a broader view of the interpolator performance, as measured by point based, jack-knife cross- validated residuals, both in geographical (across England and Wales) and temporal (annual averages rather than individual dates) extent. The geographical distribution of the *annual* averaged daily residuals from interpolation, together with the annual variance in these daily residual values at the cross-validated locations (Figure 4-24 to Figure 4-27) are used in order to identify any patterns that might assist in improving the combined covariate/interpolation model. The focus is placed entirely on the results from interpolation using partial thin plate splines following the quantitative evidence of the preceding Section 4.1.3, as this will be the chosen method for the remainder of the study. This analysis will enable the spatial distribution of these annual average residuals for daily maximum and minimum temperatures to be compared with those of the phenology model results run over the same calendar year (1976) in future chapters.

The annually averaged daily residual (bias) for each station within the sample set is plotted for maximum temperature within Figure 4-24, with the variance of the residuals at the meteorological sites over the year mapped as Figure 4-25. Locations where the model performs most poorly (both under and over-predictions) are summarised within Table 4-3. Particularly striking is the coastal nature of all of the sites with greatest negative bias (over-prediction by the interpolator), the majority of which (with the exception of Bognor Regis) are exposed southerly or westerly coast cliff top stations. In general, warm Gulf Stream air might be expected to increase temperatures close to the west coast during winter and this factor has been encapsulated within the guiding covariates. In these cases reported in Table 4-3 however, these over-estimations suggests that the sheer cliffs are increasing the 'exposure' of the sites and consequently decreasing the observed maximum temperatures. Hough (1998) for example quotes UKMO data for Cornwall that suggest that 10% decreases in wind speed at a height of 2m may give rise to temperature increases of between 0.07 °C and 0.6°C at 0.6m above the ground. Similar, if less pronounced, effects may be seen on the Yorkshire coast at Scarborough and Whitby. While not proximal to cliffs, Bognor is relatively sheltered from westerly and south-westerly winds by Selsey Bill, which at other locations might be expected to bring relatively warm onshore air under winter conditions. Since the effect of the coastal covariates is computed on a national basis, and at the majority of sites are successful, local coastal situation may explain the over-prediction at Bognor

Table 4-3. Poorest performing locations for maximum temperature predictions, by (a) average bias and (b) annual variance in bias. Red notation implies under-prediction by the interpolator, and blue refers to over-predictions.

(a)

Meteorological station	Bias
Bardsey Island	-0.85
Bognor Regis	-0.74
Gwennap Head	-0.59
St. Catherine's Point	-0.57
Manchester Weather Centre	0.61
Cardington	0.67
Scilly (St. Marys)	0.9
Valley	0.97

(b)

Meteorological station	Variance
Dungeness	1.75
Folkestone	2.13
Widdybank Fell	2.2
Bardsey island	2.35
Valley	2.45
Scilly (St. Marys)	3.64
Carlisle	4.29
Newton Rigg	5.15

Turning now to the locations where maximum temperatures are strongly under-predicted, while both Valley and Scilly (St Mary's) are coastal sites they are also both the meteorological stations for small civilian airports. Airport sites are commonly warmer than nearby (otherwise similar) locations owing to the reduction in wind speed close to temperature recorders through building location and the black body effects of tarmac. The scale of these smaller airports mean that they are not identified within the 'urban index' designed to account for these factors in large residential areas. These anomalies suggest that the incorporation of land cover information, that would allow the incorporation of local albedo within temperature estimates, would be a useful improvement to the modelling approach. However, within a multivariate linear modelling environment such as that used here as opposed to a more process-based climate model, the successful incorporation of these subtle effects may prove difficult even if the data were available.

A number of stations with high average bias also exhibit a large day-to-day variability in their residuals when considering the complete annual cycle (Bardsey Island, Valley, Scilly). Locations of different topographic character are also included within Table 4-3 as a result of their variability in residual values throughout the year alone. Through their easterly facing locations both Folkestone and Dungeness are likely to encounter a greater frequency of north-easterly winds cooled by the North Sea under anti-cyclonic conditions than for example Hastings. During the summer of 1976, such weather patterns were unusually common. These effects are also seen to a lesser degree at for example Margate and Shoeburyness, although Manston in contrast is relatively sheltered from the east (Mayes 1997) and Cromer's situation promotes strong offshore winds that restrict the influence of cooling North sea breezes (Mayes and Sutton, 1998). Covariates based upon nationally aggregated data might not be expected to pick up such differences at locations whose characteristic topography is unusual in relation to the data set as a whole. Moreover, neither the land/sea ratio or distance from the coast covariate groups incorporate direction-influenced local exposure. Exmouth and Starcross, at nearby locations at the mouth of the Exe, reveal similar aspect related differences (Figure 4-24) with the east facing Starcross consistently overpredicted and Exmouth under-predicted. Similarly, Bastreet's northern exposure may be the cause of the negative residuals for both maximum and minimum temperatures. For sites on sandy soil, such as at Dungeness and in the Breckland, high fluctuations in maximum temperature as a result of the relatively fast ground heating are to be expected. This may be the cause of underpredictions in maximum temperature, since the regression model used does not include soil type.

Poorest performance has so far been associated with sites at exposed coastal situations and airports. A further factor affecting interpolator performance identified from Figure 4-24 and Table 4-3(b) is high land. Widdybank Fell for example is one of the highest meteorological stations in England and Wales, and the sparseness of data at such heights (a function of the meteorological network rather than sampling method) makes accurate estimation difficult whatever the interpolation method. Additionally, both Widdybank Fell (Stirling 1997, p120) and Newton Rigg (Tufnell 1997) are on record as sites at which extreme low temperatures have been recorded and as such high variances in residuals at these sites are not surprising.

Turning to minimum temperatures (Figure 4-26, Figure 4-27), the poorer performance for this variable is reflected in a longer list of stations for which accuracy is particularly low or variable (Table 4-4). With the exception of St Mary's airport and Bardsey Island, there is no overlap with the corresponding table for maxima discussed above (Table 4-3) although inspection of the spatial plots reveals a number of sites with modestly strong residuals in common (e.g. Mansfield, London Weather Centre, Margate, Valley). It was affirmed that for all points over the landscape and for nine test dates, minimum temperatures were always interpolated to lower values than maxima.

Table 4-4. Poorest performing locations for minimum temperature predictions, by (a) average bias and (b) annual variance in bias. Red notation implies under-prediction by the interpolator, and blue refers to over-predictions.

(a)

Meteorological station	Bias
Hartburn Grange	-1.67
Bracknell Beaufort Park	-1.6
Scilly (St Marys)	-1.37
Bastreet	-1.37
East Hoathly	-1.17
Moel Cynnedd	-1.15
Malvern	1.07
Plumpton	1.14
Manchester Weather Centre	1.16
London Weather Centre	1.72

(b)

Meteorological station	Variance
Sandown	2.4
Bardsey island	2.55
Trawsfynydd	2.56
Marlborough	2.72
Bracknell (Beaufort Park)	2.85
Bude	2.87
Moel Cynnydd	2.88
Elmstone	3.59
Bastreet	3.94
Scilly (St Marys)	5.24

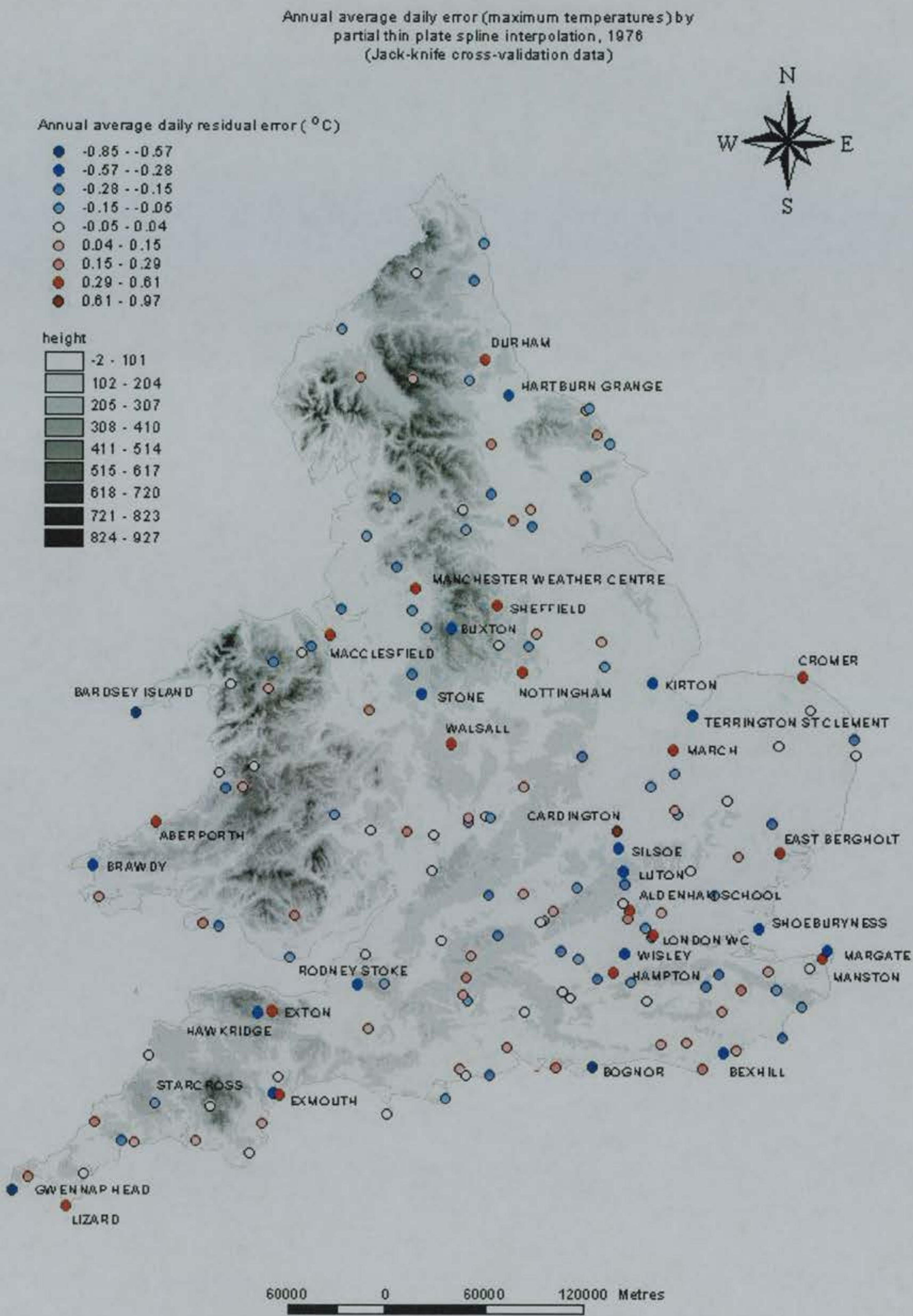


Figure 4-24. Average daily residual for maximum temperatures, partial thin plate spline interpolation, 1976

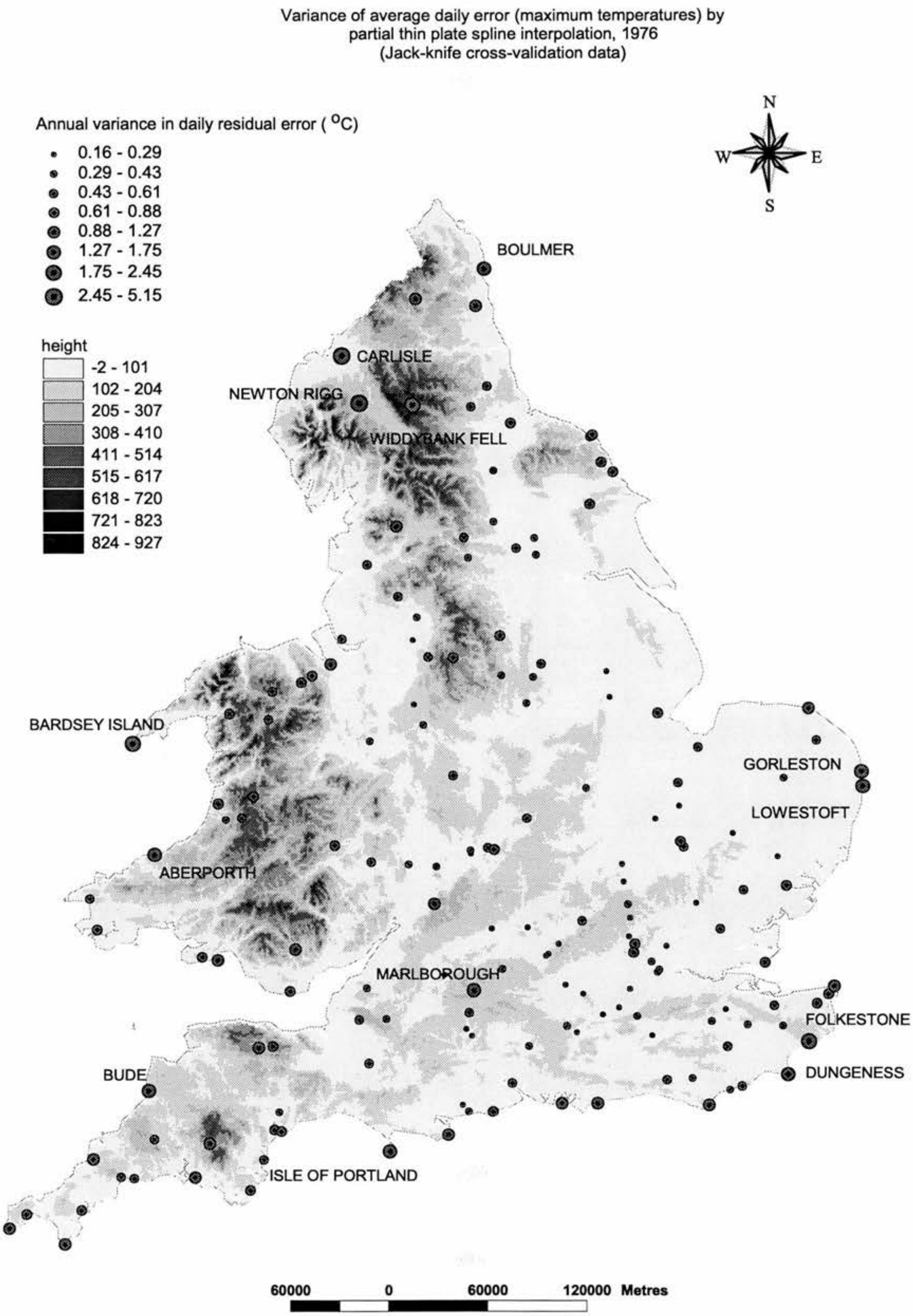


Figure 4-25. Variance in daily residual of maximum temperature, partial thin plate spline interpolation, 1976

As for maximum temperatures, problems estimating lapse rates owing to a relative lack of high elevation data occur in upland areas as exemplified by Widdybank Fell. Data in such moorland areas are also relatively sparse making higher residuals more likely in these remote areas although as Figure 4-26 shows for central-east Wales, spatially distant data alone do not necessarily lead to high residuals.

Hartburn Grange is another station known to receive cold air from the Pennines under high-pressure conditions. This situation may give rise to extreme minima, and is likely to be the cause of the high over-prediction observed in Table 4-4. Stirling (1997, p120) for example lists this site as one at which extreme national annual minima have been known to occur. In the contrasting case of Malvern however, the site is actually warmer than predicted. This may be a result of Malvern's position overlooking the Severn Valley, making it frost free in comparison to stations at lower altitudes on the valley floor (Manley 1944). Non-linearities in the 'height above basin floor' predictor variables may therefore be the cause of model under-predictions at this site.

Plotted as part of Figure 4-26 and Figure 4-27 is the urban index, in order to assist in assessing the performance of this measure. As Table 4-4 indicates, both Manchester and London weather centres show strong under-prediction relative to that expected. However, in the case of this London site in particular, the site of the recording station at roof-top elevation (as opposed to the standard flat, grassy exposure) makes these anomalies unsurprising. In future work, this is data that might be better omitted from analyses unless the data were 'regularised' prior to interpolation. Residuals for Aigburth, Nottingham and Enfield reveal an average under-prediction of minima when using the urban index in suburban locations. This suggests that the 'heat island' effect in the model may need further exaggeration.

The effects of local situation and land cover are more likely to have more influence upon minima than maxima, as seen in the cases of Moel Cynnedd and Wisley for example. For both sites, recording equipment lies within or near to woodland, and forest clearings are well known for their tendency to enhance frost. A number of stations with particular, 'non-standard' aspects also appear within Table 4-4. Plumpton for example is west facing and Trawsfynydd north facing. Managing such local scale variations is beyond the scale and national coverage of interpolation within this project, and such residuals serve to highlight the many variations in sub 1km climate processes.

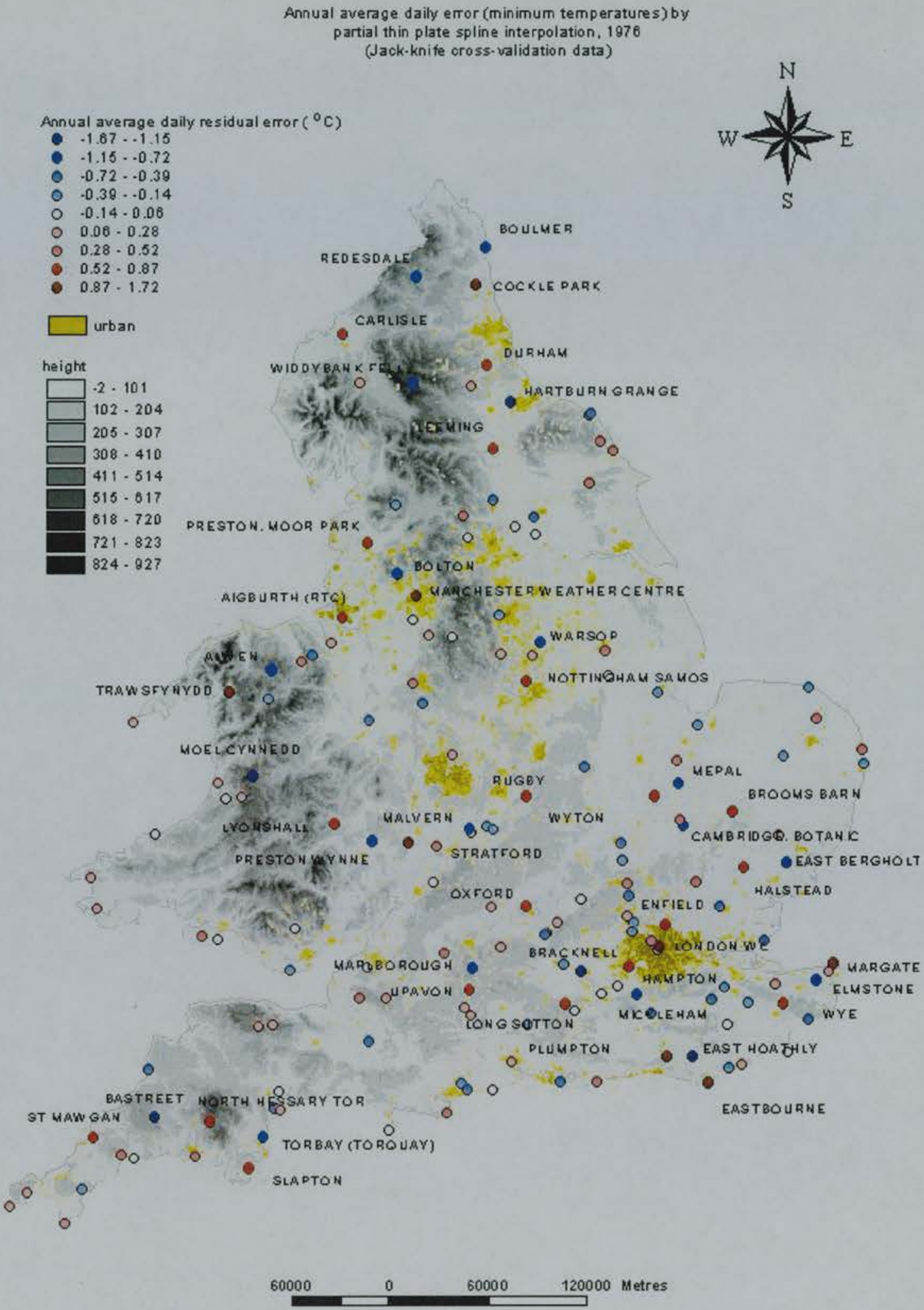


Figure 4-26. Average daily residual of minimum temperature, partial thin plate spline interpolation, 1976

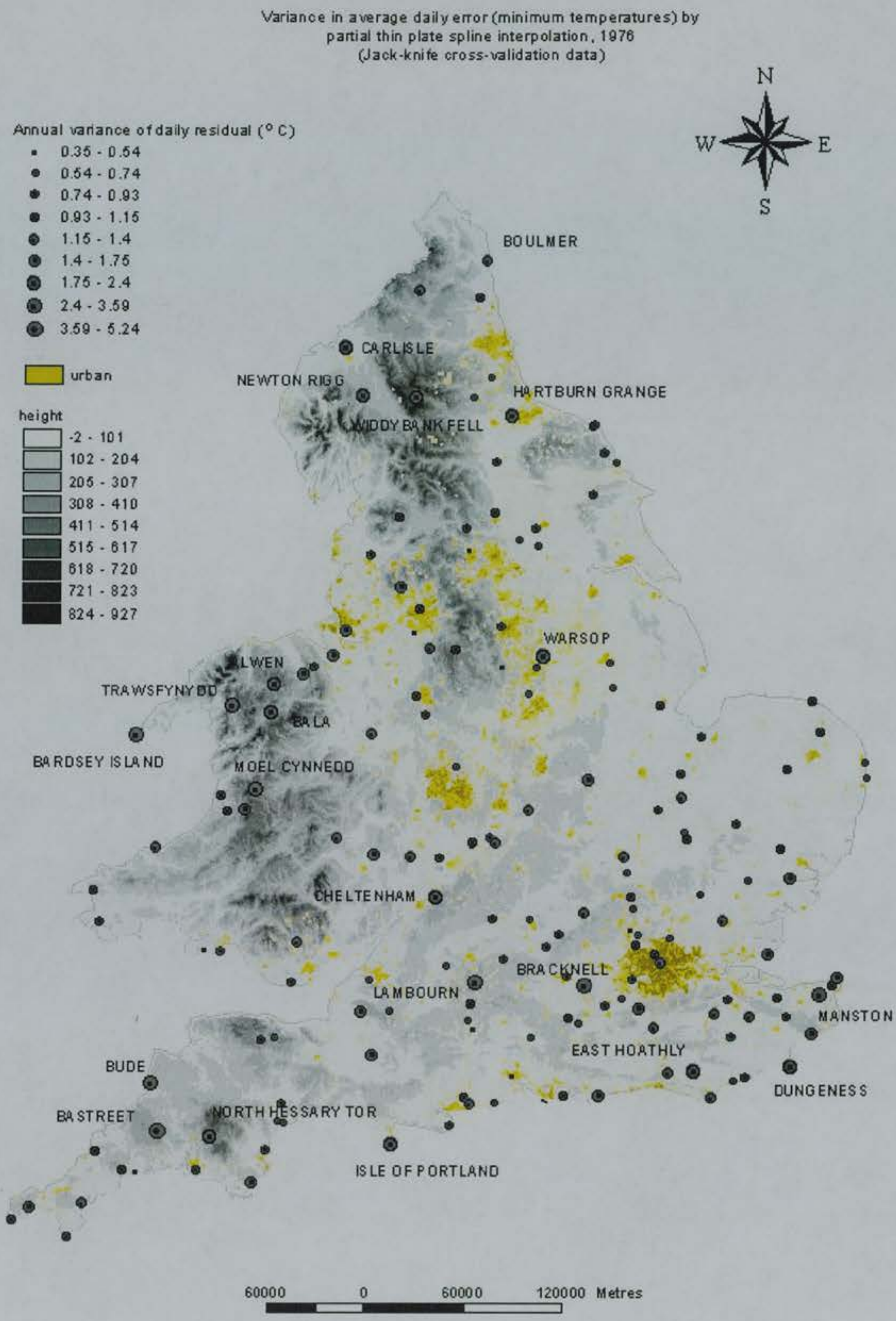


Figure 4-27. Variance of daily residual in minimum temperature, partial thin plate spline interpolation, 1976

4.2 Discussion and conclusions

Covariate analyses based upon multivariate linear modelling identified elevation, urban effects and coastal processes as particularly dominant factors affecting British daily maximum and minimum temperatures, as anticipated. Previous work taking this gridded variable based approach for daily temperature data (Cornford 1997) covered only minimum temperatures during the winter season. For maximum temperatures a lower number of terrain factors but with stronger influence were identified than for minima. The strength and direction in importance of these variables varied by season, and daily according to weather type, suggesting that adapting the manner in which covariates are used to guide interpolation on a daily basis is needed to ensure accurate estimations all year round. Other researchers such as Landau and Barnett (1996) have used a relatively inflexible trend model in a British context whatever the season, with a detrimental effect on final accuracies. Within this thesis, local regression either for covariates or the computation of interpolation parameters according to regional character was not explored given the applied phenological goal and the complexity of data management but this warrants further exploration. Additionally, problems with linear modelling of non-linear process and cross-correlated variables contributed to difficulties both in creating and incorporating guiding variables to represent minimum temperatures in particular.

Of the various significant covariates, the incorporation of an 'urban index' in order to reflect the heat island concept enabled the reduction of residuals for minimum temperatures in central urban areas relative to those reported by others such as Landau and Barnett (1996) and Lennon and Turner (1995). Temperatures remain slightly under-predicted to the outskirts of large cities, suggesting an amendment to the manner in which the index tails off in proportion to suburban landcover. As with previous studies for Britain, residual error was highest on the coastal margins even with the incorporation of multiple directional variables. Investigation of the most problematic locations suggests that incorporating coastal situation and landscape form (e.g. cliff top, aspect of the situation) would be of benefit within future work. Principal components of local terrain, used for modelling the effect of topography on rainfall in the Aurely method (Mestre 1997), or Hutchinson and Gallant's (1996) wavelet transformations of local terrain form, provide examples of the means by which the local 'shape' of the topography might be encapsulated to reduce such problems in future work. Large residuals at the highest elevations reflect extrapolation at under-represented sites within the meteorological network as a whole, but data scarcity (in geographical or covariate space) was otherwise not associated strongly with the highest estimation errors. The variability of the surface at large and small scales proved influential, with the incorporation of watershed based rather than arbitrary geometrical functions (e.g. Lennon and Turner 1995) to represent the likelihood of cold air ponding found to be beneficial at the basin scale. Considerable scope for improving the modelling of the larger scale process of cold air ponding is yet apparent, for which land cover data (unavailable to this project) would be an important component.

The size of the multivariate variable selection task, necessitating the use of automated stepwise regression procedures, exacerbated statistical problems of non-linearity, non-normality and cross-correlation between variables. Equally, difficulties in managing sequences of both daily maximum and minimum temperatures throughout the annual cycle meant that a single set of guiding covariates was selected for further use despite the variability of relationships with weather type. Variables were chosen for inclusion within the broader interpolation process on the basis of both their strength of relationship when significant and according to their consistency of selection over a sample of 63 days. Substituting multivariate regression for a feed-forward backpropagation neural network would be one means to incorporate both nominal data (e.g. weather type), to reflect non-linearities and to be more robust in the face of statistical problems and is a recommendation for further work. Neural interpolation has been explored by several other researchers as discussed within Chapter 2 (Section 2.3.2). However, it has often omitted to use surrounding data points in the process (e.g. Cheesman 1998, Dowd 1994) or to consider anisotropy (Pariente and Laurini 1993). It is suggested here that *both* spatial association and consideration of process should be used to improve interpolation. A feed-forward, backpropagation network, with its superior ability to incorporate nominal and cross-correlated data, represent non-linear relationships and provide efficient post-training outputs, might offer a suitable framework for incorporating many of these desired research strategies. Results from a pilot study linked to this work (Rigol, 1998) indicate that this neural approach has promise.

Nationwide interpolated surfaces for daily maximum and minimum temperatures on dates with different weather types would assist with the assessment of how the different interpolation methods capture the overall synoptic situation. However, for reasons associated with spatial scale the particular abilities of the different techniques in adapting to different weather conditions and spatial data configurations are masked unless extensive plots are mapped. It was decided that this volume of output would distract attention from the main focus of the thesis, but a selected number of plots for partial thin plate splines are included as Appendix 10 for completeness.

Covariate sets for estimating temperatures have been reviewed previously for daily minimum temperatures (e.g. Cornford, 1997) but the effect of incorporating increasingly detailed topoclimatic factors has rarely been consistently assessed in conjunction with different interpolation methods. Indeed, many other reviews of work interpolating temperatures report comparative results that have been made between interpolation techniques using different degrees of 'de-trending' (e.g. Bolstad *et al.* 1998). The results from this study suggest that sole reliance on the selection of guiding variables, using methods that are sometimes statistically inadequate, is a less efficient means of achieving the required accuracies than the placing of greater reliance on empirical techniques of interpolation that can account for known autocorrelation within the temperature data. Techniques such as kriging and to a lesser extent IDW can provide satisfactory national estimates provided that only *major* trends have been eliminated from the data. The improved use of guiding variables narrows the gap between interpolator performance considerably, although more sophisticated interpolators require fewer covariates in order to achieve similar accuracies.

In addition to adaptability within the covariates, automatic parameter derivation is important as part of the interpolation procedure in achieving the flexibility and robustness required for daily usage. The results suggest that automatic variogram modelling followed by kriging, despite its theoretical detractors, provides results that are competitive with those of partial thin plate splines. Improving both the computational efficiency of this task, and also the manner in which surface anisotropy is captured, are areas worthy of further study. For all interpolation techniques, partial thin plate splines included, parameter estimation was unsuccessful on a minority of dates. An improved sample of data at short lags in particular, together with an increased volume of data overall, might assist with this problem given the national extent of the study and the limited size of data set available for use (174 points).

Comparisons between the overall accuracy of the interpolation techniques show that partial thin plate splines perform well for both maximum and minimum temperatures. The r.m.s. values reported within Figure 4-13 of 0.8°C for maximum temperatures and 1.14 °C for minima compare well with other results from the literature. Landau and Barnett (1996) for example report r.m.s. accuracies of 0.96°C and 1.25°C for maximum and minimum temperatures when interpolating using a slightly large number of sites (212) for 1987. Their results for 1985 were slightly better (0.91°C and 1.07°C respectively), indicating the dangers of over precise comparisons between different data sets and years. This suggests that the performance of the minimum temperature model in this study was, in relative terms, a little poorer than anticipated. However, the r.m.s. errors reported within Figure 4-13 were produced using jack-knife cross-validation procedures while Landau and Barnett's were not independent of those used for modelling either in a true or mathematical approximation sense. Landau's error estimates were based on a subset of only 22 (randomly selected) data points, and the standard deviation in error reported within Figure 4-13 for minimum temperature in particular is considerable. Cornford's (1997) bootstrapped estimate of winter minima of 1.16 °C is more comparable with the jack-knife approach of this study (1.01°C), since both assessments were made using semi-independent cross-validation techniques (Section 3.3.3.1). However, Cornford was working to a landscape resolution of 500m and used greater volumes of data and more supporting land cover information. Validation issues are discussed in greater detail within chapter 5.

More generally, comparisons between partial thin plate splines and ordinary kriging are unusual, as are those using 'optimal' inverse distance weighting. This is especially the case within the context of an applied agricultural study, where traditional methods are most commonly used. This is believed to the first comprehensive comparison between the techniques for interpolating daily maximum and minimum temperatures, while partial thin plate splines have only occasionally been explored on a local basis for daily temperatures previously (Laughlin *et al.* 1993).

Previous work using interpolated temperatures to model spatial phenologies at $1km^2$ resolution (Russo *et al.* 1993) used trend surface interpolation as the sole method. In that case, a first degree trend plus a linear covariate for elevation were used to model both maximum and minimum temperatures over a widespread area of mixed elevation of north-eastern USA. However, validation was carried out only of the phenological predictions, rather than the underlying temperature estimates themselves. Bolstad *et al.* 's work (1998) interpolating temperatures, targeted at a phenological audience but not explicitly linking biological models with the interpolated results, used a two dimensional trend plus linear lapse-rate and compared this with methods based only on lapse-rate. For the complex British situation, the findings to date and the results and additional findings contributed by this study suggest that such a model would give rise to considerable inaccuracies relative to those achieved in this thesis.

A side product of this work has been to construct software that provides a coherent set of traditional but sophisticated tools for interpolation which are not found together in one place elsewhere. This provides a potential platform for the development of an 'intelligent' interpolation module that would assist users in their otherwise repetitive search for the 'best' model. Little guidance on this selection procedure is found within proprietary GIS and interpolation packages, and 'rules of thumb' (e.g. approximately 150 points are required in order to construct robust variogram) are scattered very widely within the literature. While the naïve user would be assisted by the heavy use of automatic fitting procedures within GEO-BUG (e.g. the automatic selection of power parameters for inverse distance weighting), the efficacy of these procedures should nevertheless be checked for each application. Inadequate or no de-trending may for example have deleterious effects on variogram construction prior to ordinary kriging that may not be immediately apparent within the resultant grid. These type of issues have been identified as priorities for basic research within the environmental modelling community (Burrough, 1992) whose long-term goal includes the creation of more 'intelligent' systems to support environmental decision-makers (Densham and Goodchild, 1989).

4.3 Chapter summary

- The sequence of daily maximum and minimum temperatures for the year 1976 were interpolated over England and Wales to a resolution of $1km^2$ using partial thin plate spline, ordinary kriging, trend surface and automatic inverse distance weighted interpolation;
- A wide variety of land cover and topo-climatic covariates were derived and explored to find the best subset of variables that could be used throughout the year to guide the interpolation process for both daily maximum and minimum air temperatures. Previous work taking this gridded variable based approach (Cornford 1997) has covered only minimum temperatures during the winter season;
- Covariates chosen as a result of multivariate linear modelling included elevation, urban land use, coastal factors and topographic variability. Previous work interpolating daily and monthly temperatures has often ignored the potential impact of urban development on minimum temperatures (e.g. Lennon and Turner 1995, Landau and Barnett 1996);
- Strength of relationship and consistency of selection of variables varied considerably by season

and weather type, necessitating the adaptive parameterisation of the regression coefficients on a daily basis;

- Differences between interpolator performance, measured in terms of the accuracy of estimations on the basis of jack-knife cross-validated residuals, were reduced by including increasing numbers of covariates;
- Given that each covariate incorporated was known to be significantly related to temperature, this suggests that the inclusion of values from nearby meteorological stations into the estimation of temperatures is a more efficient means of achieving greater accuracy than increased attention to the selection of additional guiding variables. The benefit of increasing the number of covariates was more marked for the less sophisticated interpolators (e.g. trend surface analysis);
- Parameters of the interpolation methods were successfully selected using 'automatic' methods for inverse distance weighting, kriging and partial thin plate splines for the majority of dates;
- The calibration of interpolation parameters for kriging and IDW would be improved with extra data from meteorological stations, especially for short lag separations;
- The accuracy of the estimations of temperature by the various methods of interpolation were assessed using jack-knife cross-validation on the basis of aggregate statistics and the spatial variation in residuals;
- Best accuracies were achieved using partial thin plate splines, with r.m.s. error for maximum temperatures of 0.8°C and 1.14 °C for minimum temperatures. This is a slight improvement in accuracy over the previous limited literature on interpolating daily temperatures;
- Rarely have partial thin plate splines, ordinary kriging, automatic inverse distance weighting and trend surface interpolations been compared, especially within an applied agricultural context;
- The national coverage and annual sequence over which the interpolations were validated is unusually thorough;
- The use of guiding covariates would be improved through the use of techniques that are not as reliant on statistical assumptions, allowing for example the incorporation of nominal variables (e.g. weather type), non-linearities and robustness to cross-correlation. Neural networks, with their analogies with non-linear regression and function free adaptive nature, might provide one means of achieving these goals;
- Analysis of the residuals from partial thin plate spline interpolation suggest that the incorporation of coastal shape and situation, land cover and soils data might improve the modelling of local-scale climate processes.

5 From temperatures to phenologies

5.0 Introduction

The estimation of temperature itself, discussed in the previous chapter, is not the end research goal of the thesis. Rather, these temperature surfaces provide a source of geographically referenced inputs to phenology models, which predict the rate of development of insect according to temperature (Section 2.1.2). This chapter begins by illustrating the different types of output that may be produced using the research system developed. This will familiarise the reader with the various phenological constructs used in later chapters. Throughout this discussion, all the phenologies constructed have been modelled by using interpolated temperatures as the input to the pest models. The effect of this interpolation strategy, compared to the approach of interpolating the outputs from phenology models run only at sites where meteorological records are available, will be analysed within Chapter 6. This section of the chapter concludes with comment regarding the system design, and on the capabilities and weaknesses of this research prototype in relation to previous work in the domain (Section 5.2).

The second part of the chapter explores the validation of the pest phenologies estimated in this way and attempts to clarify how errors in the individual daily estimates of temperature may propagate and possibly compound over longer periods (Section 5.3). These results are expressed in terms of pest development levels, or dates at which a certain stage of development is reached. The overall distribution of cross-validated error results and their degree are reported (5.3.1.1), as is their geographical pattern (Section 5.3.1.2). Additionally, the effect of increased attention to detail regarding the interpolation of temperatures on the error propagation within the biological models is investigated. Questions such as 'to what extent are more sophisticated interpolation methods for temperature warranted?' are explored using aggregate results for England and Wales. These issues are all exemplified using results from the accumulated temperature model for consistency and transparency, since the accumulated temperature model is the most straightforward in the way it relates to pest development. This also avoids overlap with later discussions of the way in which modelling results may be applied in practice (Chapter 7).

To this point within the thesis, all validation of the model results has been reported on the basis of jack-knife cross-validated residuals. A further tranche of temperature data for 120 sites over England and Wales (Figure 3-6), made available in the final stages of the work, was used to assess differences between jack-knife cross-validated results and fully independent testing. Comparative results are reported for both the individual input temperature layers (Section 5.3.3.1) and the modelled accumulated temperatures (Section 5.3.3.2). This theme of assessing error follows through to the final portion of the chapter, where the commonly suggested practice (e.g. Robeson and Willmott 1993) of interpolating the residuals from an interpolation process to provide an 'error surface' is assessed quantitatively.

5.1 Assessing the research framework: phenological outputs

The research prototype enables the following categories of output files to be created, according to the particular program module specified (Chapter 3, Figure 3-22):

- Gridded phenologies;
- Temporal, point-based, pest development sequences;
- Jack-knife cross-validated residual error at data points.

As explained within Chapter 3, loose-coupling between biological models and GIS was selected for research implementation. ASCII-based files of outputs from the phenological models for accumulated temperatures, Colorado beetle and codling moth were manipulated using proprietary software, for example EXCEL™ spreadsheets or ARCVIEW™/ARC-INFO™/GRASS GIS systems in order to visualise and explore these results.

Fedra (1993) suggests that '*Visualisation provides the bandwidth necessary to understand large amounts of highly structured information, and permits the development of an intuitive understanding of processes and interdependencies, of spatial and temporal patterns, and complex systems in general.*' While the focus of this work is not visualisation per se, graphics are used to demonstrate the nature and variety of uses of the outputs. While the three major categories of results above may be produced for each type of phenology model linked within the system, the manner in which these results are used may be different according to their practical use in either IPM or PRA. Outputs are ordered by the three phenology model types to allow visual associations between the different forms of results to be made, a strategy termed *'associative exploration'* by Beard and Buttonfield (1999).

5.1.1 Gridded phenologies

Effective, strategic assessment of pest risk requires the ability to make consistent national estimations rather than those limited to a limited number of local areas. The capability of the research software to produce the nationwide variability in pest risk from year to year is illustrated within Figure 5-2 for the accumulated temperature model. Results for 1976 and 1986 (Figure 5-2) represent degree-days accumulated in years of unusually hot and cold summer temperatures within the climate normal period (1961-90). Using temperature as a guiding basis, these two maps can provide indications of the maximum and minimum extents over which a non-indigenous pest might thrive. In a strict statistical sense, these model results are not directly comparable since the location of the underlying meteorological station data vary slightly from year to year. Nevertheless, these changes in station position are unavoidable for any long-term analysis of pest data. The ability to plot out these geographical ranges and to begin to infer the potential for pest development at locations over different years is a significant advance over previous approaches to spatial pest risk assessment that used long term average climate data. While temperatures exceeding a base temperature of 8.5° have been accumulated in these particular examples in an effort to mimic a pest whose survival is marginal under

British climatic conditions, the user may select the most pertinent base temperature for their task as input to the modelling system. Data summarising appropriate base temperatures and thresholds for many pests may be found on the Internet (e.g. Appendix 5) that could be used to undertake a variety of risk assessments and to develop a variety of risk scenarios using the new software. Coverage over the United Kingdom demonstrated within Figure 5-2 represents a post-thesis extension of the modelling suite to run using geographical (i.e. degrees of latitude/longitude) co-ordinates in addition to a standard national grid referencing system used elsewhere within the thesis. The capability to explore nation-wide variation in geographical pest risk has not previously been seen at this spatial scale ($1km^2$).

'Fully spatial' gridded model output is demonstrated in detail using two $100km^2$ case study areas in Kent and North Yorkshire. Both areas are mapped at a resolution of $1km^2$. Kent is one of the major areas of apple orchards in Great Britain. This is thus a particularly pertinent area in which to explore the spatial phenologies of codling moth, which is a major pest of apple crops. The characteristics of this study area will be introduced within Figure 5-4. Looking more closely at the plots for Kent, Figure 5-6 for codling moth underlines the dominance of the time in insect development. The plots show the dates on which 50% of an original (static) population are predicted to reach each major developmental stage, mapped to the same date intervals throughout the lifecycle sequences. Greater variation may be seen within the range of dates over time than within any one spatial representation, although this varies with model characteristics. For codling moth for example, there is least variation at the larval stage (Figure 5-6 (c)) for which the rate of development with temperature is slow (Figure 3-6 p 76) and the phase of development short.

In a PRA context, it is most likely that Colorado beetle would establish first around the ports of southern Britain should any future arrivals be uncontained within the port areas. Nevertheless, this area of Yorkshire has a strong arable farming heritage and potatoes are grown in both lowland and foothill areas within the Vale of York (Figure 5-7), providing an interesting location at the margins for survival of Colorado beetle. More generally, the principles used to create spatial phenologies and their relevance for the timing of control treatments have application to a wider variety of agricultural pests rather than just for the Colorado beetle. A similar picture to that for codling moth in regard to development at different locations in space within a small area emerges in the case of Colorado beetle (Figure 5-9). The precise date of adult maturation is very temperature sensitive, such that minor temperature differences within the landscape result in big differences in state at certain times of the year. The dates by which the different stages of insect development are reached are mapped for each stage using an identical legend to illustrate the relative importance of time versus space by insect form. The relative distinctiveness of geographical pattern within the image reflects the importance of the temporal dimension, which may be interpreted as more dominant where the range in Julian dates for the image is limited. This use of a standard legend across all stages of development however blurs the real spatial patterns detectable within the individual images, and therefore the importance of differences in development dates across the geographical areas on a day to day basis.

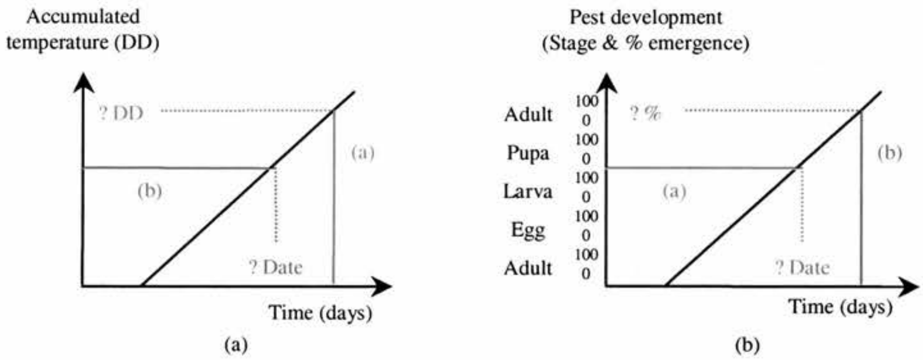


Figure 5-1. Flexible, 'two-way reporting' of biological model results for accumulated temperature and phenology models. Primary queries reported shown in red and labelled (a), secondary queries in blue and labelled (b).

The importance of geographical variation in phenologies is more clearly seen within Figure 5-11 which maps the percentage emergence by day over a period of potential rapid development in the summer months at a time in which the potato crop is vulnerable to attack. This shows a variation of 45% in the emerged percentage of larvae over the Yorkshire area in the period 28-30 June 1976. Many pests need control applications to be very carefully targeted to percentage emergence, often to particular larval instars rather than the complete larval phase. Such geographical differences in the dates at which stages are attained could therefore be significant in terms of their biological application, and confirm the value of exploring the spatial dimension often ignored by traditional biological models. Both this (Figure 5-11) and Figure 5-3(b) demonstrate the flexibility provided to construct the biological model results according to purpose. While a standard request when using the codling or Colorado beetle models might be to ascertain the date at which the pest reaches a predefined stage and emergence level of a particular stage (Figure 5-1(b), pest development), Figure 5-11 demonstrates that it is also possible to map the emergence percentages on specified dates. Similarly, Figure 5-3(b) maps the date at which a particular accumulated temperature threshold is reached rather than the accumulation of temperature by a specified date as demonstrated in red within Figure 5-1((a), accumulated temperature).

The research software allows sequences of grids by day, as discussed above. These may be displayed side by side (as in Figure 5-11(a-d)) or by means of a movie as exemplified for vine weevil (Morgan and Jarvis 1999) in order to explore the temporal dimension of pest development. Given the complex interplay between geographical and temporal dimensions of pest development, some care is needed in both the construction and the subsequent interpretation of these new geographical phenology maps. Where the speed of development is particularly rapid, differences in space may be small relative to those in time. Archiving daily gridded outputs for model runs of up to 1½ years in length would consume large volumes of computer memory during computation and retrieval and disk space for storage. The temporal sequences explored need usually to be limited in either space or time, and often both. Use of this dynamic visualisation capability therefore needs to be targeted on the basis of previous explorations of the snapshot, 'year-end' phenology grids according to geographical areas showing interesting features and through the use of the time-series outputs (Section 5.1.2) to identify particularly significant periods within a pest's lifecycle.

5.1.2 Multi-temporal, point based, pest development sequences

Results from phenology models have traditionally been communicated to the biological research user by graphing development progress for each insect stage throughout the period of the model run, typically a calendar year. However, in the few cases where the geographical differences in such computed rates have been considered, this has been confined to an analysis of the different estimated development of a pest at the point location of the meteorological stations where input data for the model was available. In contrast, results from the research software developed for this project may be produced for any 1km^2 cell within the modelling landscape (e.g. Figure 5-8, Figure 5-5). These figures plot pest development as a proportion of an original (nominal) population reaching a particular stage throughout the duration of the model run. Thus, for every 1km^2 within England and Wales, a characteristic time-series graph exists. Figure 5-7 and Figure 5-8 viewed together exemplify the differences in development curves that arise even within local areas.

Turning to the temporal sequences illustrated for Colorado beetle and codling moth, considerable differences may be identified between sequences plotted for the locations within Figure 5-7 and Figure 5-4 respectively. For Colorado beetle, for example, up to 15 days difference in larval development for the Colorado beetle between potato growing locations within the Vale of York may be identified. Differences of 15 days in the larval development times for codling moth within Kent during 1976 (Figure 5-5) were also found. Many pests, Colorado beetle and codling moth included (Section 2.1.1.1), are best controlled during this relatively vulnerable stage, but only a very limited number of chemical applications in particular are allowed per season. Without targeting the application in *both* time and space, the effectiveness of a treatment may be restricted, in turn leading to re-application and increased potential for a pest to develop resistance.

These time-series graphs also provide a view of generational cycles that may be masked by the standard outputs from many models, such as those produced by PETE. The PETE model (used for Colorado beetle) produces outputs by development stage, but not (as in PESTMAN, used for codling moth) explicitly distinguishing the possibility of multiple *generations* of the same stage occurring within the model run. Identifying the potential number of generations of a pest that may occur within a season (e.g. within Figure 5-8) is important evidence within a formal pest risk assessment.

5.1.3 Cross-validated error

Within chapter 3, a method was discussed for computing jack-knife cross-validated residual errors within the spatial phenological results. These residual errors arise from uncertainties in the process of interpolating temperatures used to extend the phenological estimates away from meteorological stations (Figure 3-17). There will always be some error associated with such a process, and it is vital to measure this to ensure that the nation-wide geographical estimates fall within acceptable limits for practical purposes. Examples of false confidence and over-security in computerised maps abound, and the intention is that, to use Henderson-Sellers' (1996) terminology, the software should be seen as a 'heuristic tool' rather than a 'truth machine'. Explicit provision of residual and r.m.s. errors, even if partial when considering the multiple sources of uncertainty, reduces the possibility of model outputs being misinterpreted and the accompanying caveats being ignored or blurred.

The results of the cross-validation program within the research software are ASCII files listing station location, the actual result at that site based on the known temperatures at that point, the estimated phenology and the residual (actual - estimated value). The nature of these residuals will vary according to the model under consideration, but always relate to a particular 'snapshot' of spatial phenology requested. For both codling moth and Colorado beetle examples, phenological outputs are expressed in terms of expected emergence dates. Residuals in these cases are therefore measured in numbers of days. In the case of accumulated temperature, outputs are expressed in accumulated °C, or 'degree-days' and so, therefore, are the residual errors. From such files, these residual data may be treated in a similar fashion to independent validation data, and either mapped or used to construct aggregate statistics such as the r.m.s.error ($\sqrt{((\sum \text{residual}^2)/n)}$) of the combined n locations as desired.

Figure 5-10 illustrates the distribution of residuals (number of days error in estimated emergence date) for estimates of the date Colorado beetle larvae reach 50% emergence of both their egg and larval stages over the 174 locations where meteorological data was available. No consistent over or under estimation in the number of days over the country taken as a whole (bias) arises, although individually for a number of locations estimates are both early or late by up to half-a-month in a minority of cases. Consideration of whether these modelling accuracies are adequate for biological use will be critically discussed within the context of their particular applications in Chapter 7. General issues relating to evidence of geographical bias or emergent spatial patterns of interest within the residuals are explored more generally for the accumulated temperature model within Section 5.3.1.

Accumulated temperature

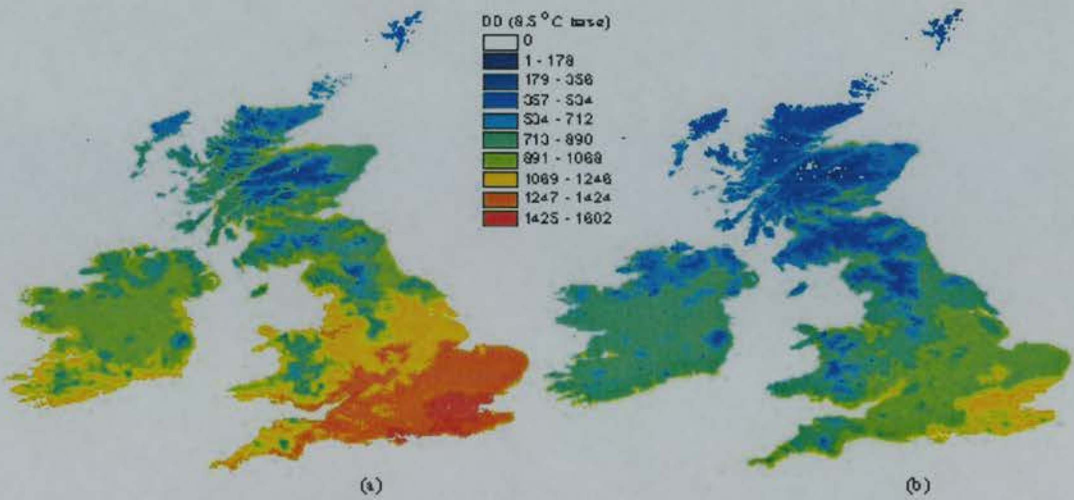


Figure 5-2. Accumulated temperatures (Base 8.5°C) over the United Kingdom, (a) 1976 and (b) 1986

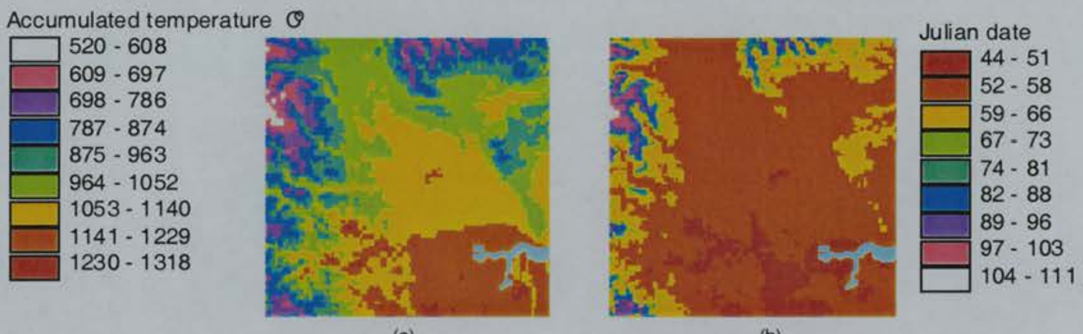


Figure 5-3. (a) Estimated accumulation of temperatures (°C) using UK Meteorological Office method (Anon, 1969) with base temperature 8.5°C and (b) date at which 230 accumulated °C threshold for larval development is reached, Vale of York, 1976

Codling moth

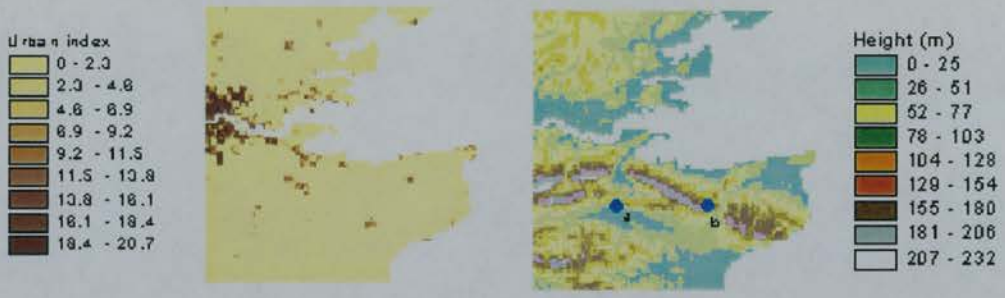


Figure 5-4. Height and urban index, Kent

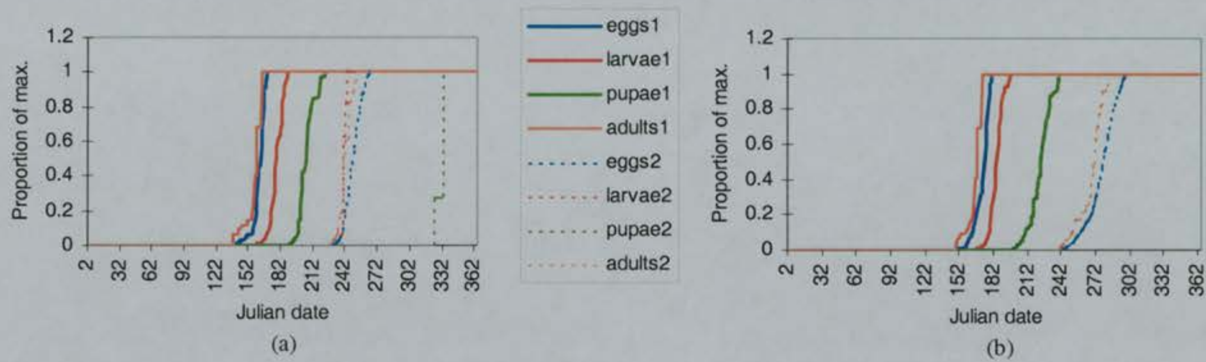


Figure 5-5. Lifecycle development of codling moth, Kent. First and second generation insects at sites (a) and (b)

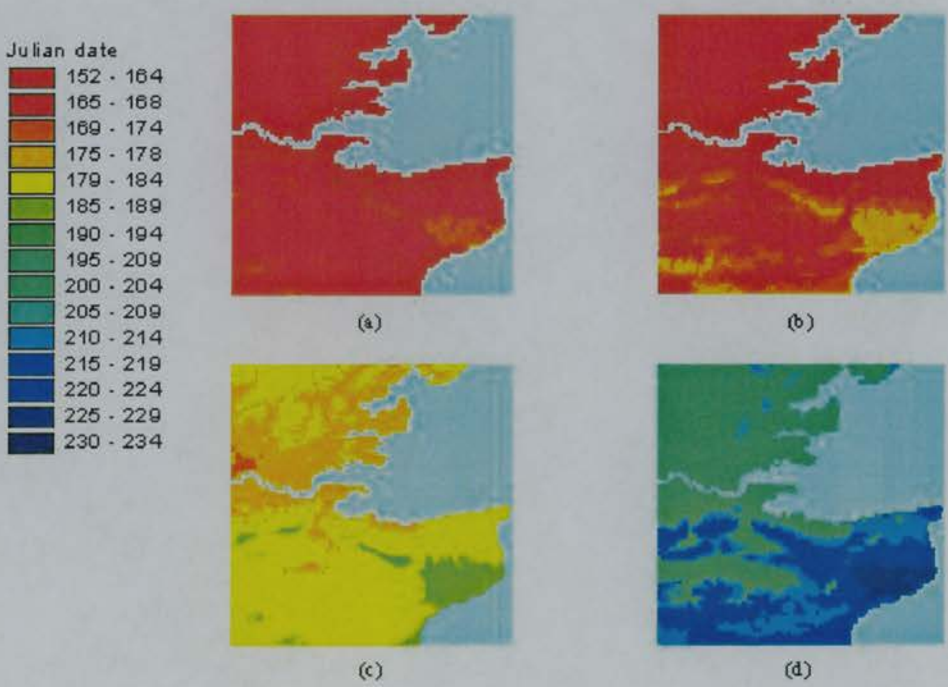


Figure 5-6. Estimated Julian dates for 50% emergence of codling moth (a) mature adults, (b) eggs, (c) larvae and (d) pupae, Kent, 1976

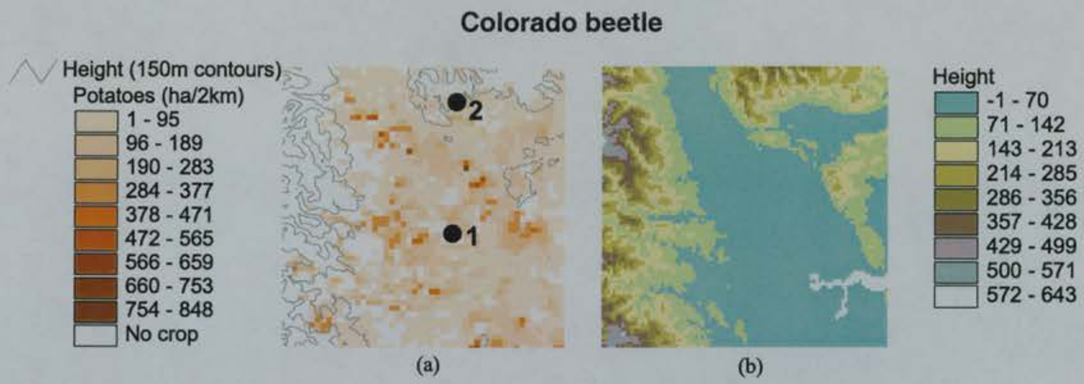


Figure 5-7. (a) Distribution of potato crop (1994) and (b) elevation, Vale of York

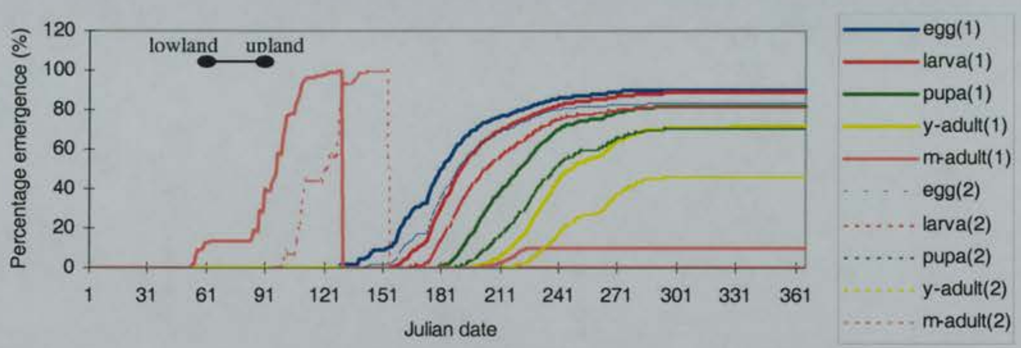


Figure 5-8. Estimated life-cycle development throughput the year 1976 for Colorado beetle at upland (2) and lowland (1) sites marked within 5-7, Vale of York (dashed curves - second generation development)

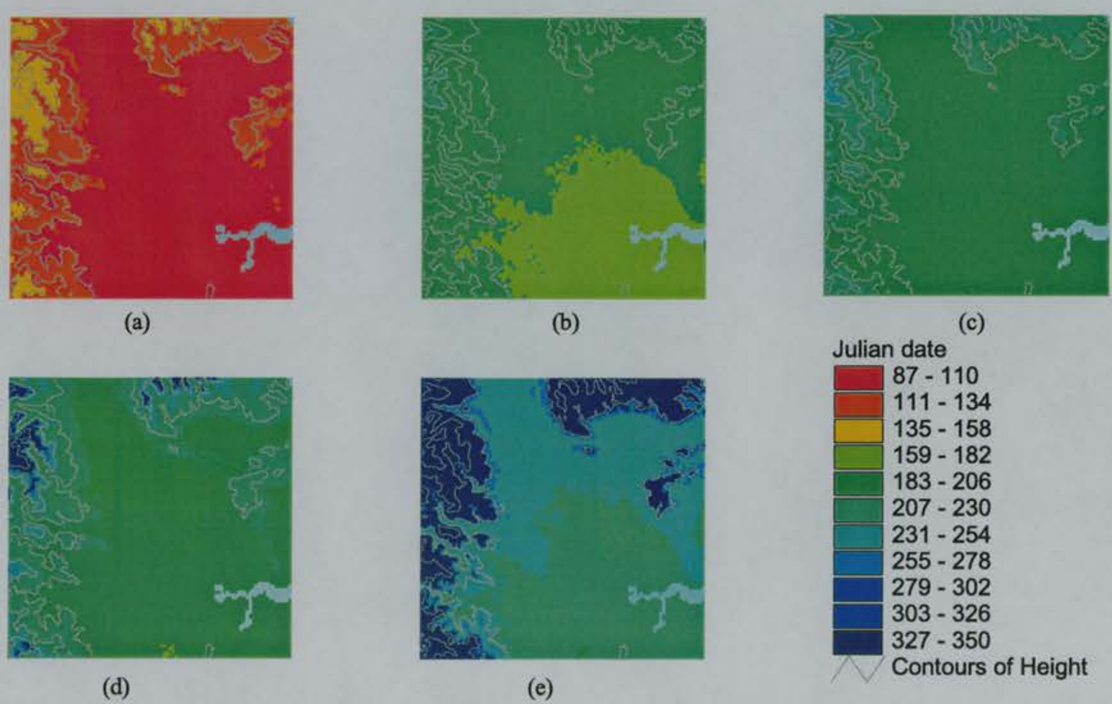


Figure 5-9. Estimated Julian dates for 50% emergence of Colorado beetle (a) mature adults, (b) eggs, (c) larvae, (d) pupae and (e) young adults, Vale of York, 1976

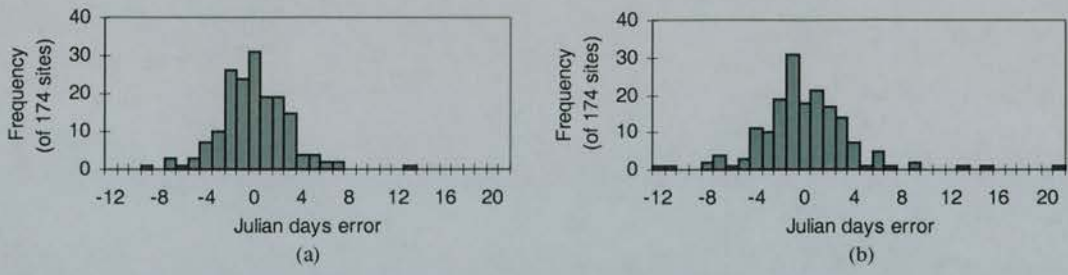


Figure 5-10. National estimate of cross validated error, Colorado beetle 1976 (a) 50% emergence adult stage and (b) 50% emergence egg stage

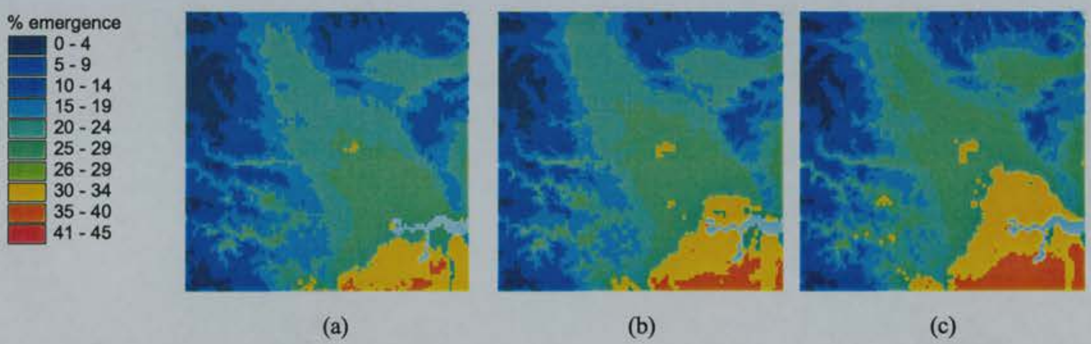


Figure 5-11. Estimated percentage emergence of larval stage, Colorado beetle, Vale of York, 28-30 June 1976 (a)-(c)

5.2 Assessing the research framework: discussion

The types of output facilitated by this research software provide several additional research tools to explore the spatially distributed phenological results in comparison with previous work. Closest in form is Régnière *et al*'s *BIOSIM* (1996). Régnière's work, which allowed the coupling of different models within a pragmatic system to interpolate and output continuous surfaces of phenological model results (rather than temperature surfaces, as in this case), formed part of a large campaign that aimed to eradicate the gypsy moth from the forests of NE America. Indeed, much previous work looking at landscape-wide insect ecology in general has focused on forest pests such as gypsy moth, and as such this study represents a departure from earlier research. Similarly to BIOSIM, one of the benefits of the system developed here is that its design, although not object-oriented in approach, allows the linking of different models with varied output characteristics (Figure 3-21, p122).

The ability to explore phenological development over time at all or any particular location comes as a by-product of the modelling of spatial phenologies by means of interpolated temperature surfaces (Figure 3-20, p121). As Figure 5-5 and Figure 5-8 showed, considerable variation in development cycle may occur even within localised areas that, in the absence of locally relevant temperatures with which to run the phenology models, has not been explicitly identified in previous work. Régnière (1996) and Schaub *et al* (1995b) for example produced their distribution maps of insect phenologies by interpolating the results of their phenology models obtained at the meteorological stations, rendering this output option infeasible. Additionally, these pest development sequences are the same output as produced by the original point based software (Section 3.1, p71). The time-series graphs therefore provide a useful bridge between the previous aspatial phenologies and the 'fully spatial' results of this thesis for biological users unfamiliar with geographical concepts. The recent Danish Pl@ntInfo Internet advice site, with a similar graphing facility, demonstrates that this utility is of practical value to agricultural advisors. However, the spatial resolution provided by Pl@ntInfo is crude in comparison to the $1km^2$ grid achieved within this project, and the results are combined on the basis of data from the nearest meteorological station to the grid square rather than the more locally relevant interpolated temperatures as in this case.

Previous attempts to create what are termed here '*geographical phenologies*' have been reliant on independent sample data for the biological validation of the results. When assessing the 'fitness for purpose' of spatial phenologies targeted at specific management tasks, the use of independent data provides an important combined estimate of both error arising within the geographical modelling and the biological modelling. Arguably, such independent data also provide the most objective or accepted test of a model's accuracy. This will only be the case however where sufficient test data are available. Régnière (1996) sampled 5 points over area of varied terrain in the Appalacians (100 * 150km), while Bolstad *et al.* (1996) assessed their results for interpolated temperature on the basis of data from only four locations across four American states. Bolstad's validation data set in particular is arguably too low. For this study in contrast, accuracy estimates at 174 locations over Britain were facilitated through cross-validation at the original data points, allowing an improved assessment of spatial reliability. This is important when considering the case for the approach taken within this thesis to be more widely adopted within agricultural DSS. The use of jack-knife cross-validation within the thesis allows error to be estimated at any point through the pest's lifecycle, rather than solely at 'trappable' stages. Moreover, where non-indigenous pests are concerned as for much of this thesis, field sample data are inevitably unavailable to test the results. These two approaches do however reflect different but complementary measures of the overall uncertainty associated with spatial phenologies. Colour maps can be persuasive, and any methodology that aims to provide more objective 'scientific' supporting evidence on pest development that might be used as part of a PRA for governmental purposes needs to be assessed for its accuracy. Jack-knife cross-validation serves to fill this gap. Additionally, for exploratory analyses rather than solely pragmatic purposes, identifying the error relating to the geographical approach in particular rather than the combined biological/geographical modelling components is better achieved using jack-knife cross-validation and a deterministic biological model. This issue will be further discussed in the context of potential applications of this work to IPM (Chapter 7, p245).

The research question 'can spatial phenologies be explored using the capabilities of proprietary GIS?' was answered within chapter 3 by the description of the FORTRAN based research software (p119) that was required to perform the core interpolation and modelling tasks. GIS served mainly as an adjunct, managing the data storage and permitting the visualisation of the geographical results. This confirms Goodchild's (1993) proposition that policy-driven applications are more likely to require loose coupling than other, less involved, applications. Additionally, as Gillick (1999) demonstrated using the GEO-BUG code as a base, Windows-based GIS programming languages can be used to develop basic 'front-end' systems to support the visual browsing and exploration of spatial insect phenologies.

The technique developed within the thesis that allows models to be run over large areas by separating the functions that evaluate the underlying interpolation equations (e.g. 'automatic' daily variogram models, spline surface equations) from those that compute the interpolated results at specific points provides it with a fundamental advantage. This is realised both in the ability to compute daily series of phenological development at any cell location in the modelled landscape, and also within the capability for the efficient computation of jack-knife error estimates for any specified target output. The design of the software allows the results for individual grid squares of phenological output to be computed for the complete time series in turn, without either the re-computation of the basic geographical model or the unnecessary re-working of 'nearest neighbour' functions on different days at identical locations. The method therefore reduces both computation time and the working memory required for the combined interpolation and modelling task, which otherwise might prove prohibitive. Without such a structure, exploring the differences between interpolating the results from phenology models versus interpolating temperatures as input to a phenology model run multiple times over space would not be possible. Further exploration of this interpolation/modelling strategy issue is found within the following chapter, which focuses on the effects of using these two strategies from the perspective of error propagation.

A further advantage of the system developed for this research is the incorporation of a variety of interpolation techniques, both sophisticated and traditional, within the one framework. Previous work modelling spatial phenologies has, without exception, reported results on the basis of a single, traditional interpolation method. Bolstad *et al.* (1996), Régnière (1996) and Schaub *et al.* (1995b), as reported in Chapter 2, focus on trend surface analysis alone. Approaching the problem for the first time from a geographical perspective rather than a biological research angle has allowed more systematic analyses of these interpolation issues, and the potential for considerable differences between methods has been thoroughly examined. Comparative results between techniques for interpolating temperature (Section 4.1.3, p144) have found trend surface analysis to be the least accurate of the four methods implemented in this thesis. The effects of the different interpolators upon the accuracy of estimated phenologies will be discussed later within this chapter (Section 5.3.2).

Comparison between the interpolation methods of partial thin plate splines and ordinary kriging within an applied research project is unusual beyond this study of insect phenology. This owes much to differences in their theoretical stance and background of the two 'schools' behind the methods (Section 2.3.2, p50). However, these two methods of interpolation may be formally linked through their dual equations (Appendix 4). This means that, as Hutchinson and Gessler (1994) note, generalised covariances may be substituted for spline basis equations within the code for splines and then solved more efficiently than for the covariance components of kriging. Equally, splines may be substituted into the covariance part of kriging since all of the commonly used spline basis functions are valid generalised covariances (Cressie 1991, p180). Using such overlaps to maximise the reusability of the individual software modules, both at this theoretical level and at the level of the matrix computations used by all interpolation techniques, was not however a priority within the thesis and would have involved significant re-coding. Considerable scope exists for improving the efficiency of the software developed, since redundancy is implicit as a result of combining public domain code from multiple sources. From a research perspective however, results were attainable within a reasonable time period using the framework which served its purpose in providing a means of generating results for scientific analysis that was not otherwise feasible using proprietary tools. Testing has shown the system to perform robustly in the case of both specifying the underlying variables (Section 4.1.2, p137), selecting the interpolation parameters automatically for each day and the combined interpolation/modelling of results. Detailed assessment of error in the interpolation and modelling follows within the second half of this chapter.

For further development of the software for operational applications, it will be desirable to expand the scope of the modelling beyond the consideration of temperature based phenologies to incorporate additional variables such as rainfall and relative humidity affecting crop diseases. Incorporating extra variables as multiple model inputs will necessitate improved efficiencies such as the use of dynamic memory allocation (not available within FORTRAN 77 used in this work). As a general platform for comparing interpolation methods for individual variables, and enabling interpolated data to be passed through a biological (or other) model, the system designed has considerable scope for further use in other studies. Currently, the software runs on the basis of command line prompts that may be bundled within UNIX scripts to ease the running of multiple experiments. Scripts for running standard requests within the pest risk assessment context for example have been collated within a series of user manuals, ordered by biological model (Jarvis 1999). To increase accessibility to the general user, a user-friendly interface could be built using a visual programming environment that allows access to existing graphing and mapping functionality (e.g. Microsoft Excel™ and ESRI MapObjects™) while facilitating background access to a UNIX server running the basic program suite. Initial explorations using ARC-VIEW™ as a front-end for the system for pest risk assessment tasks (Gillick 1998) suggest that that this mapping software presently lacks the flexibility required, especially for charting and graphing, given the complexity of pest risk applications. The scope of possible interactions currently feasible within the software means that tailoring of such an interface to the task anticipated (e.g. general interpolation suite, pest risk analysis, integrated pest management) would require careful analysis of user requirements.

5.3 Error propagation and validation

5.3.1 Spatial phenologies: propagation of error

As outlined within Chapter 3 (Figure 3-17) and demonstrated within 5.1.3 for Colorado beetle, jack-knife cross-validated temperature estimates may be propagated through the phenological models to provide estimates of the errors in the biological outputs that similarly may be considered mathematically independent. This section focuses on both the summary statistics of the residual errors (e.g. r.m.s. errors, overall bias) and the spatial configuration of such errors as propagated through the accumulated temperature model. Analysis of the accumulated temperature results avoids complications with calendar date and allows errors to be assessed more straightforwardly in terms of their overall distribution and bias, both in 'aggregate' (all spatial locations together) and over space. Results for the more complex codling moth and Colorado beetle results are reported in greater detail within chapters 6 and 7.

Within this section, results are divided according to discussion of:

- Aggregated residuals

  The combined distribution of residuals (actual – jack-knifed model estimates) from all 174 locations for accumulated temperature estimates, where degree-days have accumulated throughout the calendar year 1976;
- The spatial distribution of model residuals

  Residuals (actual – jack-knifed model estimates) of accumulated temperature model estimates, where degree-days have accumulated throughout the calendar year 1976;
- The effect of interpolation technique used for modelling temperatures on the accuracy of the accumulated temperature estimates for the calendar year 1976.

5.3.1.1 Aggregated residuals

The distribution of residuals for accumulated temperature results at the end of runs of the degree-day model for 1976 and 1986 are illustrated within Figure 5-12 and Figure 5-13. Accumulations over bases 5°C, 8.5°C and 10°C are illustrated to reflect the range of probable errors in estimated expected development for both indigenous (lower base) and non-indigenous (higher base) pests.

Figure 5-12 and Figure 5-13 illustrate a small positive bias in the distribution of values of the residuals of between 4.5 to 6 degree-days (DD) for results of all bases and both years. In comparison with the overall range in residuals, which varies between 339 to 574DD subject to base temperature and year, this overall bias is slight suggesting that the overall modelling system neither over or under-predicts accumulated temperatures on average. Accompanying this bias is a positive skew for all but residuals from 1976 over base 8.5°C, with residuals more strongly peaked towards mean values for 1986 data.

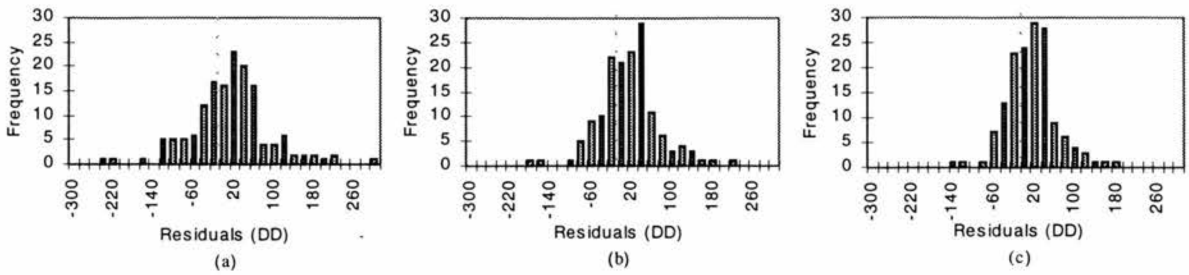


Figure 5-12. Accumulated temperature cross validated r.m.s. error, (a) Base 5°C, (b) Base 8.5°C, (c) Base 10°C, (1976)

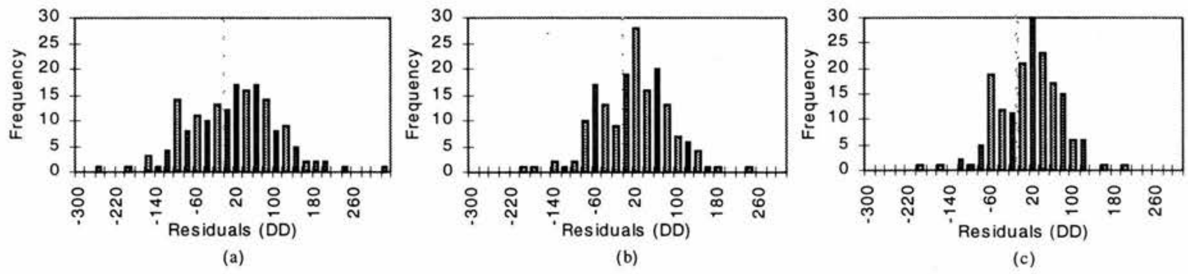


Figure 5-13. Accumulated temperature cross-validated residual errors, (a) Base 5°C, (b) Base 8.5°C, (c) Base 10°C, (1986)

Overall, residuals are greatest for 1976, which given the tendency for error to increase with average temperature (Figure 4-17) is to be expected. Differences in the range of error decrease with increasing base temperature, owing to the greater number of days over 5°C relative to 10°C within any year. For 1986, which exhibited cool summer temperatures relative to those of 1976, this decrease in error range is exacerbated. In terms of their application in pest risk assessment the overall confidence limits on the distributions for accumulated temperature are encouraging at all bases and for both years. 95% of the values are accurate to within 13 DD for the model run over an entire year (albeit a slightly non-normal distribution). The practical significance of this value is likely to depend on when within the lifecycle the majority of errors accumulate, a subject returned to in greater detail within Chapter 6. Both maximum and minimum extremes within the residuals are however high relative to the length of an insect's lifecycle, making the location of such extremes an important next question to explore.

5.3.1.2 Spatial distribution of errors

The spatial distribution of residuals computed by cross-validation for the accumulated temperature model running over the base temperatures 5°C, 8.5°C and 10°C for the calendar year 1976 is illustrated within Figure 5-14. The modelled ('actual') values of accumulated temperature at the points where meteorological records are available are coloured using the same scale as that used for the ('estimated') interpolated surface in order to highlight any major discrepancies, while spatial variation within the residuals themselves is shown using a relative bipolar legend.

The location of the most extreme residuals is summarised within Table 5-1. Following Appendix 5 degree-days accumulate with average temperature unless temperatures fluctuate around or below the base value. The sites within Table 5-1 might therefore be expected to match those poorly performing stations from Table 4-3 and Table 4-4 for maximum and minimum temperatures, especially locations where minima are particularly poorly estimated and those locations where residuals for *both* temperature variables are relatively high.

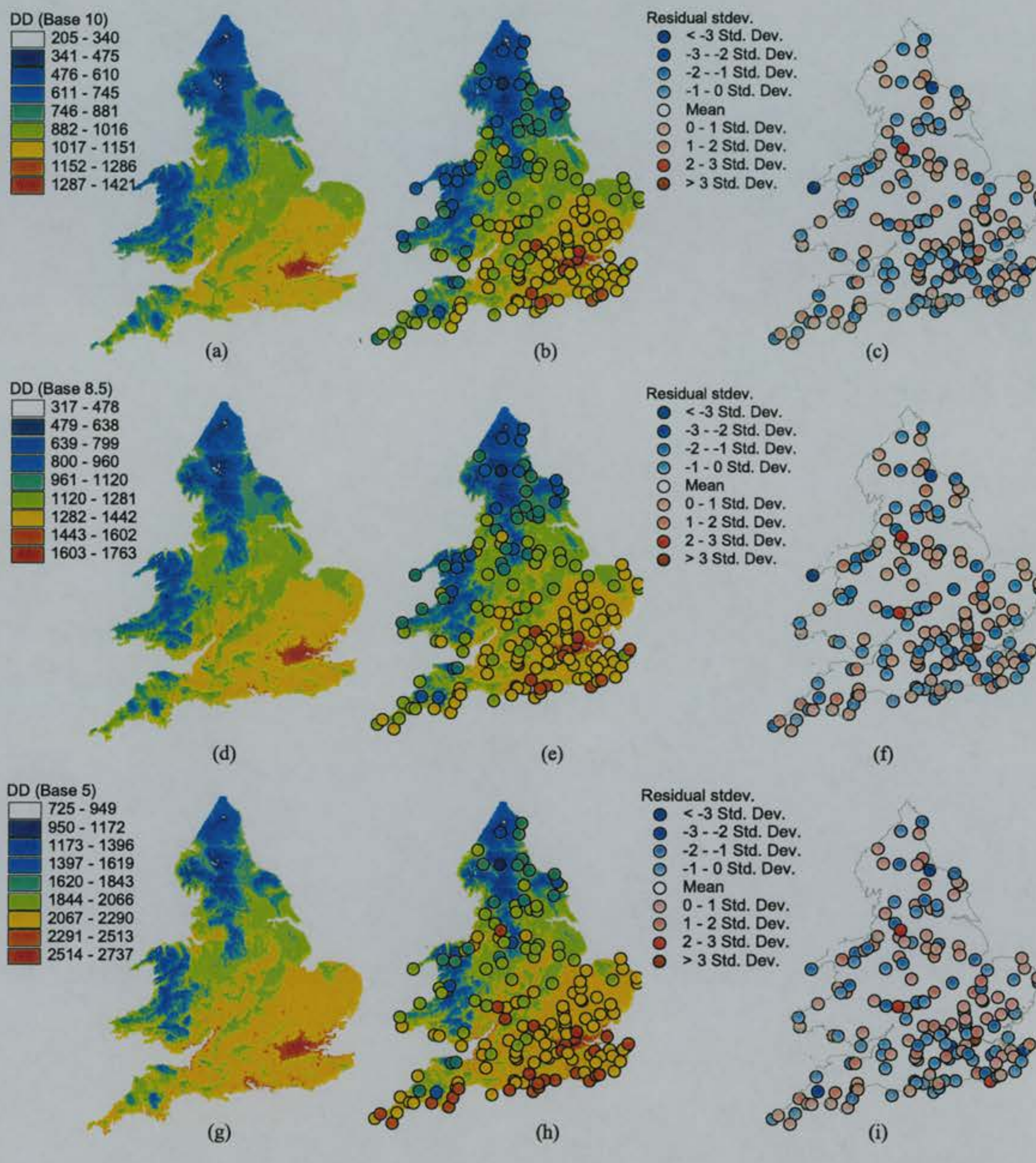


Figure 5-14. Estimated surfaces of accumulated temperature (a,d,g), estimated surface with point actuals overlaid (b,e,h) and spatial distribution of cross validated residual errors, degree days over base temperatures 5°C, 8.5 °C and 10 °C accumulated over the calendar year 1976

As would be expected, a number of the stations reported with high residuals in accumulated temperatures match those of Table 4-3 and Table 4-4 showing strong residuals for maximum and minimum temperatures respectively. While three stations with particularly poor performance for interpolated maximum temperatures (Bardsey Island, Manchester Weather Centre and Valley) from Table 4-3 appear within Table 5-1 however, nine locations from Table 4-4 are represented. This adds weight to the suggestion that even small differences in ability to interpolate temperatures (0.806°C for maxima versus 1.141°C for minima) *are* exacerbated when propagated through a phenology model as an annual series of daily data.

Table 5-1. Best and worst performing stations for accumulated temperature model (in decreasing order of absolute residual) 1976

	1976	
Base 5°C	Base 8.5°C	Base 10°C
London weather centre	London weather centre	Bardsey Island
Hartburn Grange	Bardsey Island	London weather centre
Manchester weather centre	Hartburn Grange	Hartburn Grange
Bracknell, Beaufort Park	Manchester weather centre	Manchester weather centre
Malvern	Bracknell, Beaufort Park	Elmstone
Eastbourne	Elmstone	Bracknell, Beaufort Park
Elmstone	Malvern	Malvern
Bastreet	Eastbourne	Ryde
Plumpton	Ryde	Manston
Bardsey Island	Manston	Valley
St. Mawgan	Hawarden Bridge	Eastbourne
Ryde	Marlborough	Marlborough
Bolton	St. Mawgan	Hawarden Bridge
Hawarden Bridge	Plumpton	St. Mawgan
Marlborough	Bastreet	Plumpton

Stations identified as having poor residual temperatures that do not appear to affect accumulated temperature strongly include Bognor, Gwennapp Head, St Catherine's Point, Cardington, Scilly for maxima and in addition East Hoathly, Scilly and Moel Cynnedd from the list of minima. Reference to Figure 4-24 and Figure 4-26 suggests that the reason for these stations absence is that, with the exception of Scilly, in no case do extreme residuals for *both* maxima and minima coincide.

As a corollary, a number of stations are identified within Table 5-1 that do not present with large residuals for either maximum or minimum temperatures within chapter 4. These include Eastbourne, St Mawgan, Ryde, Bolton, Hawarden Bridge and Manston. Inspection of Figure 4-24 and Figure 4-26 reveals that at these locations residuals for both maxima and minima follow the same sign, and that in all cases one of the two residuals is particularly strong if not extreme. Where sites have large residuals, but their direction is opposing, errors cancel within the averaging process of the accumulated temperature model. This result however is likely to be strongly model specific, and in many cases where different processes are affected by maximum or minimum temperatures independently or temperature thresholds are used, model errors might be expected to follow the location of extreme residuals in temperature more closely.

Running the accumulated temperature model at different bases alters the configuration at the lower end of Table 5-1 slightly, although the poorest performing stations are consistent through all the results. Substitution rates are low, with Bolton appearing in the table at a base temperature of 5°C, Manston at 8.5°C and Valley at10°C. This is suggestive of differences in seasonal prediction ability at these sites, with Valley performing particularly poorly during the summer months relative to these other stations, and Bolton the most stable of the three in its annual variation of residuals. Figure 5-15 confirms this to be the case for maximum temperatures in particular.

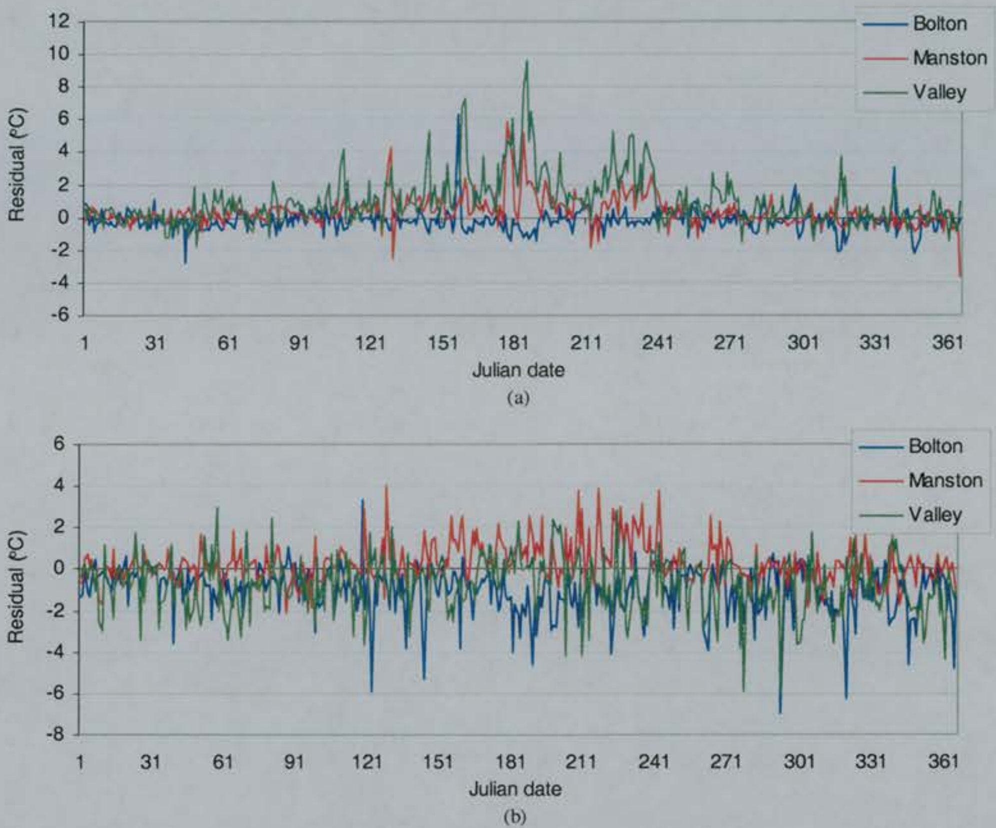


Figure 5-15. Jack-knife cross-validated residuals (°C) in (a) maximum and (b) minimum temperatures, 1976, at Bolton, Manston and Valley

The temporal element within this spatial error distribution is further reinforced by examination of the comparative residuals for Figure 5-17). While the distribution of underlying data for 1986 (151 data points) is not exactly the same as for 1976 (174 data points) owing to shifts within the underlying meteorological network (Figure 5-16), differences in the distribution of residuals go beyond those expected on the basis of data location alone. In particular, the variances within the plots for 1986 (Figure 5-17) are markedly lower than those for 1976 (Figure 5-14). Given the lower summer temperatures of 1986, the lowest variability Figure 5-17(c) is to be expected following Figure 4-17 which associated larger error with higher temperatures and their variability. Of the stations highlighted as having particularly extreme residuals (**Table 5-2**), the set of stations overlapping both years includes only London Weather Centre, Hartburn Grange, Eastbourne, Ryde and Malvern.

Figure 5-16. Sites used for interpolations and modelling, 1976 and 1986

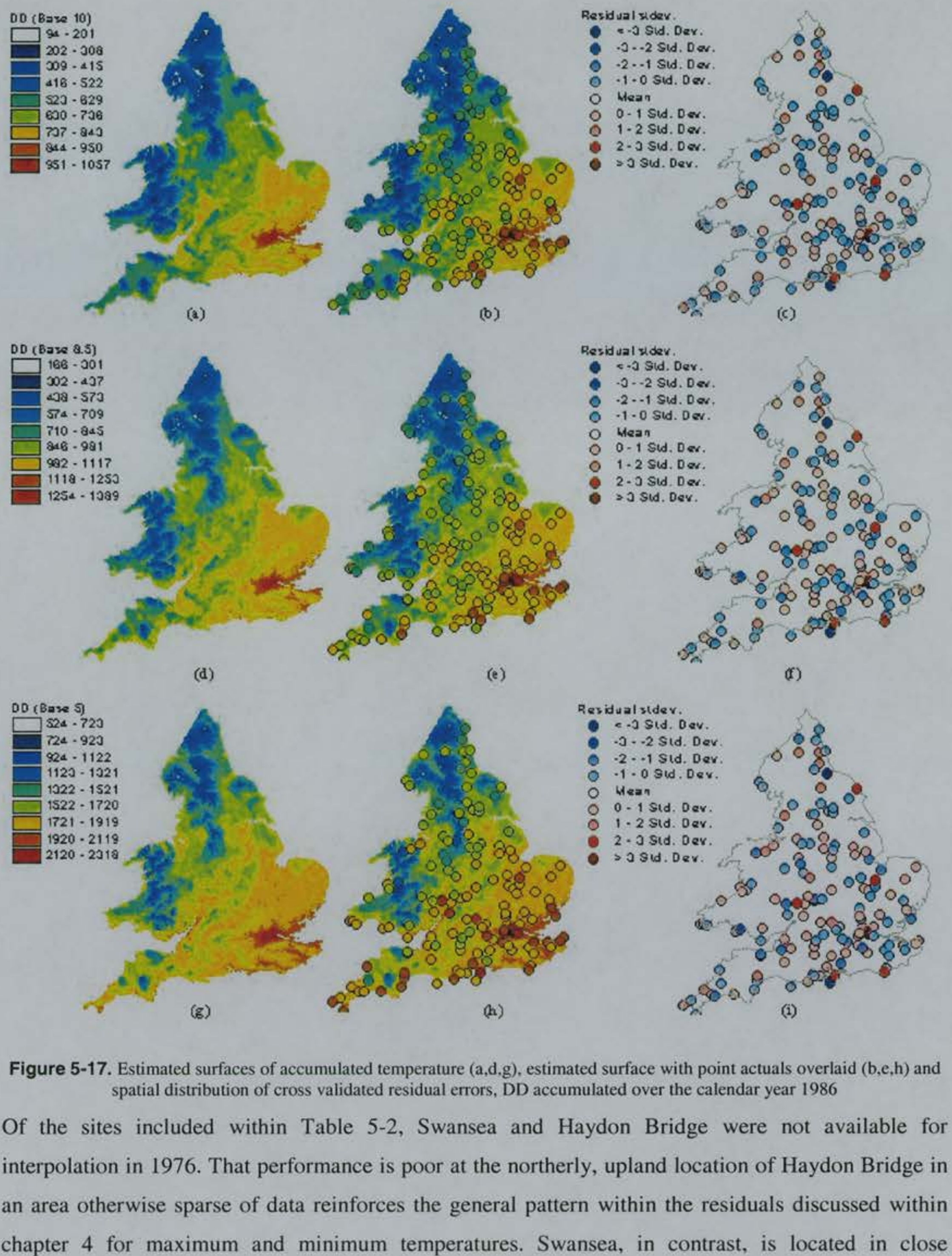


Figure 5-17. Estimated surfaces of accumulated temperature (a,d,g), estimated surface with point actuals overlaid (b,e,h) and spatial distribution of cross validated residual errors, DD accumulated over the calendar year 1986

Of the sites included within Table 5-2, Swansea and Haydon Bridge were not available for interpolation in 1976. That performance is poor at the northerly, upland location of Haydon Bridge in an area otherwise sparse of data reinforces the general pattern within the residuals discussed within chapter 4 for maximum and minimum temperatures. Swansea, in contrast, is located in close proximity to both Penmaen and Mumbles Head on the Gower Peninsula and the second two sites were also included within the 1976 analyses as having large residuals. This confirms the importance of local aspect in mitigating or emphasising the influence of prevailing weather patterns, and the variable nature of the emergent error patterns according to time-variant weather systems in addition to data configuration.

Table 5-2. Best and worst performing stations for accumulated temperature model (in decreasing order of absolute residual, red +ve, blue -ve) 1986

1986 Base 5°C	 Base 8.5°C	 Base 10°C
London weather centre	London weather centre	London weather centre
Hartburn Grange	St. Catherine's Point	St. Catherine's Point
St. Catherine's Point	Hartburn Grange	Ryde
Eastbourne	Ryde	Hartburn Grange
Ryde	Eastbourne	Eastbourne
Malvern	March	March
March	Malvern	Malvern
Scarborough	Scarborough	Scarborough
Swansea	Swansea	Swansea
Penmaen	Haydon Bridge	Haydon Bridge
Haydon Bridge	Penmaen	Ruthin
Rothamstead	Walsall	Walsall
Walsall	Ruthin	Penmaen
Stone	Rothamstead	Rothamstead
Ruthin	Mepal	Faversham

5.3.2 The effect of interpolation method and covariate choice on accumulated temperature model results

The results of chapter 4 support the use of partial thin plate spline interpolations for daily maximum and minimum temperatures. Previous work in insect ecology has however used trend surface analysis for interpolation, and from an applied biological perspective it would be valuable to know what the benefit of using the more complex interpolation technique amounts to in terms of phenological accuracy. Within Figure 5-18 the r.m.s. errors in degree-days for accumulated temperatures over the base temperatures of 5 °C, 8.5 °C and 10°C are plotted according to the technique by which the driving temperature values were interpolated, and by the number of guiding covariates incorporated as part of the interpolation process.

At each of the three base temperatures, the error in accumulated temperature was greatest when using the local methods of interpolation (kriging and automatic IDW) to drive the biological model. This difference amounted to a difference in r.m.s. error of approximately 8DD, whatever the underlying base temperature. For a base temperature of 10°C (Figure 5-18(a)), error in the results for trend surface interpolation decreased steadily with increased number of guiding covariates for the interpolation of temperature, throughout the covariate set. In contrast, at the lower bases this improvement of accuracy with increasing number of covariates stabilised at approximately the third covariate only (Figure 5-18(b),(c)). This suggests that the guiding variables selected were particularly appropriate for conditions in the hottest of summer months for both maximum and minimum temperatures. This finding was obscured within the analyses for temperature, since accuracies for the *combined* interpolator and covariate effect were plotted on a daily basis (Figure 4-20, Figure 4-21).

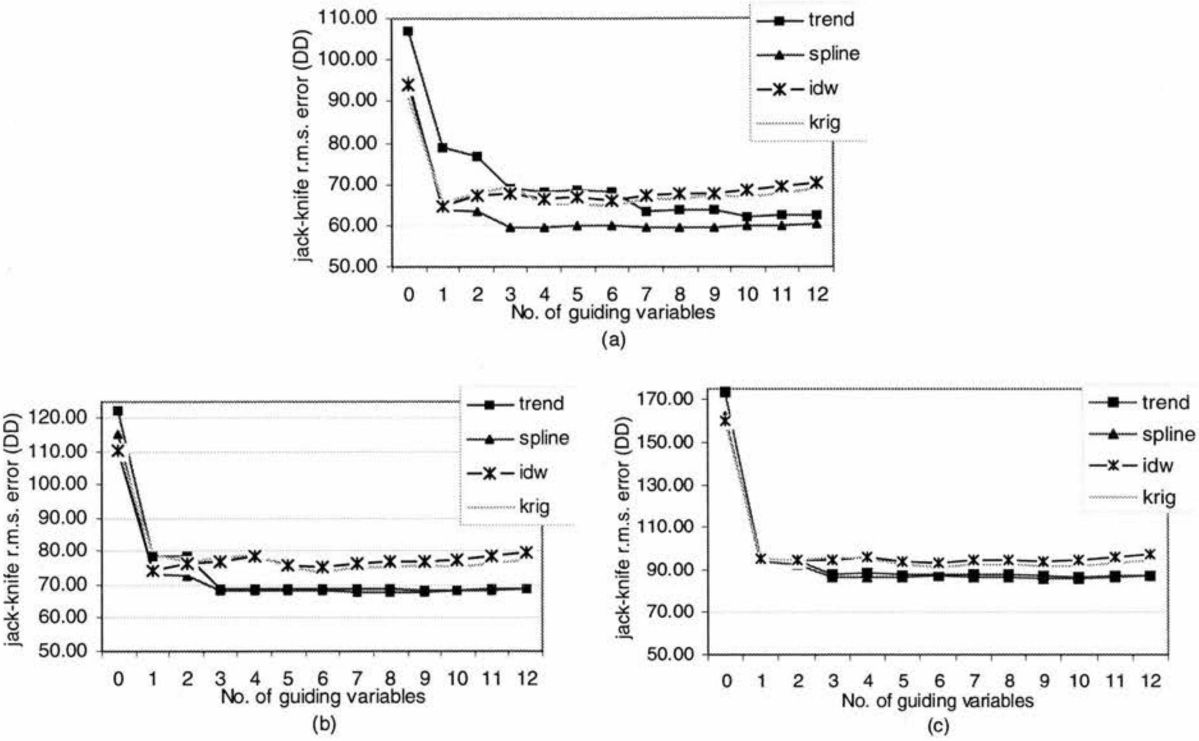


Figure 5-18. r.m.s. accuracy (DD) for accumulated temperatures, 1 January 1976 – 31 December 1976, (a) Base 10°C, (b) Base 8.5°C and (c) Base 5°C

The rationale behind the relatively poor performance of kriging in comparison with the trend surface results in particular is less easily explained. When examined from a perspective of the relative performance between interpolators, as opposed to absolute degree-day difference, the results for local interpolators become increasingly similar with decreasing base temperature. It would appear that the local adaptivity of the interpolators better compensates for the poorer winter performance of the guiding covariates and possibly adapts better to local frontal conditions which are more varied over the country during the winter period. It is certainly the case that the local interpolators tend towards less extreme and more 'average' estimates, while the global interpolators produce the highest extreme temperatures and therefore r.m.s errors (Figure 4-20, Figure 4-21). The probability of predicting extreme values for both maximum and minimum temperatures together on any particular day however is relatively low, such that the error in the estimates of average temperature computed using the local interpolators and the global methods is similar.

5.3.3 Cross-validation versus or independent testing: comparative results

To this point within the thesis, error has been reported in terms of jack-knife cross-validated results rather through truly independent assessment. This decision was taken in the light of the relative sparseness of the data set for the nationwide interpolation task. While the computation of cross-validated errors is now common for single interpolated surfaces, the manner in which cross-validated estimates of temperature were propagated through the pest models to provide an estimate of model error in addition is unusual within the literature.

In a geographical context, comparison between these two most commonly used methods of error assessment is rare. On the basis of an additional data for 120 sites in 1976 distributed throughout England and Wales that was received at a late stage within the project, it was possible to assess the similarities between independent test data and jack-knife cross-validated results. The differences between validation methods are investigated firstly for single temperature surfaces, and secondly with respect to accumulated temperature results.

5.3.3.1 Temperature input surfaces

Daily r.m.s. errors for maximum and minimum temperatures, computed using identical methods but firstly on the independent data set and secondly by sequentially omitting one point in turn using the technique of jack-knife cross-validation, are compared within Figure 5-19. For all times of the year, for both temperature variables, the patterns of both plots are similar. However, during June, the r.m.s. error for maximum temperatures computed using the independent data set suggests considerably higher errors. In the case of minimum temperatures, occasional 'spikes' in the truly independent data assessment may be seen during the autumn and winter months in particular.

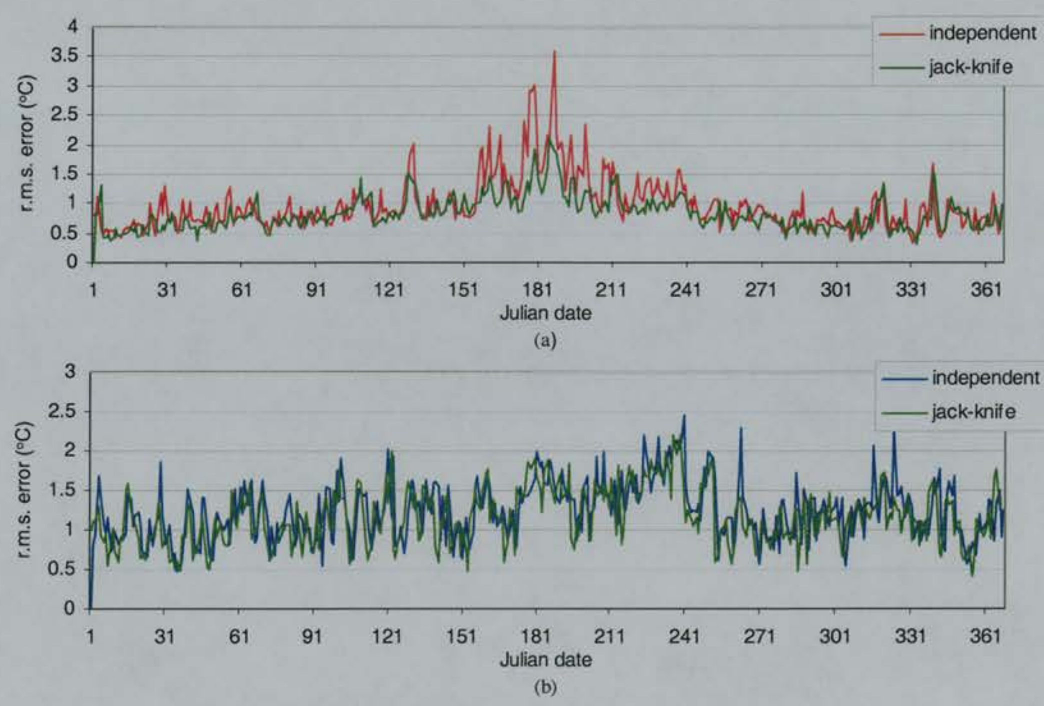


Figure 5-19. Fully independent r.m.s. error versus jack-knifed r.m.s. error for (a) maximum and (b) minimum temperatures, partial thin plate spline interpolation, 1976

On the basis of error computed using the independent data, the annual daily r.m.s. accuracies of the temperature interpolations differ significantly (95%) from the annual daily r.m.s. averages reported in chapter 4 (Section 4.1.3) of 0.80° for maxima and 1.14 ° for minima with new estimates of 0.97 ° and 1.24 ° respectively. As reported within chapter 3 however, the most reliable of data were selected during the initial phase of work. The data used for independent assessment reflects the remainder of stations open during 1976, many of which are at over-sampled coastal locations previously rejected in favour of those at high elevations or otherwise sparsely sampled areas. As the cross-validated assessments indicated, coastal stations are relatively poorly modelled in comparison with those in prime agricultural locations. Figure 5-20 to Figure 5-23 demonstrate this problem, with coastal sites particularly poorly interpolated in the case of residuals for maximum temperatures and with high variability in errors for minima. The ratio of infilling within this additional tranche of data is also high, placing further question marks against the reliability/representativeness of the actual test data.

Comparing the location of residuals of maximum temperatures from independent validation (Figure 5-20 and Figure 5-21) with those of jack-knife cross-validation (Figure 4-24 and Figure 4-25, p157), the general pattern of error shows a number of similarities. Over-prediction (negative residuals) at coastal locations on the north east coast occur in both independent and cross-validated tests (e.g. Bridlington Figure 5-20), as do those on the south coast (e.g. Brighton Figure 5-20, Bognor Regis Figure 4-24) and to the western aspect of the exposed south west peninsula (Culdrose Figure 5-20, Gwennap Head Figure 4-24). Further inland, large residuals in both directions are encountered in both plots within North Wales. Under-prediction (positive residuals) in East Anglia (Figure 5-20) is less apparent in the cross-validated results, although this is in an area where there are few stations with which to make direct comparisons. Equally, negative residuals are more apparent within the independent test data for the north east uplands although similarly this is an area of sparse data. Looking to plots of variability in the respective residuals (Figure 5-21 and Figure 5-23), greater variability is apparent for northern North Wales and the upland areas of northern England when the independent data set is used to estimate error. In comparison with central areas, difficulties interpolating coastal fringes remain whichever method of error assessment is used.

Comparative plots for minimum temperatures (Figure 4-26 and Figure 5-22 for cross-validated and independent results respectively) also reveal that both error assessment techniques produce similar results. Coastal and inland North Wales exhibit high variability within the residuals in both cases, as does coastal central Wales, the north west uplands and the Greater London conurbation (Figure 4-27, Figure 5-23). Residuals appear more severe over the Devon moors (Cheldon Barton, St Johns Figure 5-22 vs. Bastreet, North Hessary Tor Figure 4-26) within the jack-knifed plots, but this may be attributable to local situation (aspect) rather than validation method. Especially in the case of the more locally variable minimum temperatures, only general trends within the plots may be compared since the data have site specific characteristics that render over-detailed assessment between methods inappropriate. Sites have specific properties, and the sites used are not the same between methods, rendering direct comparison between methods on a station-by-station basis is infeasible.

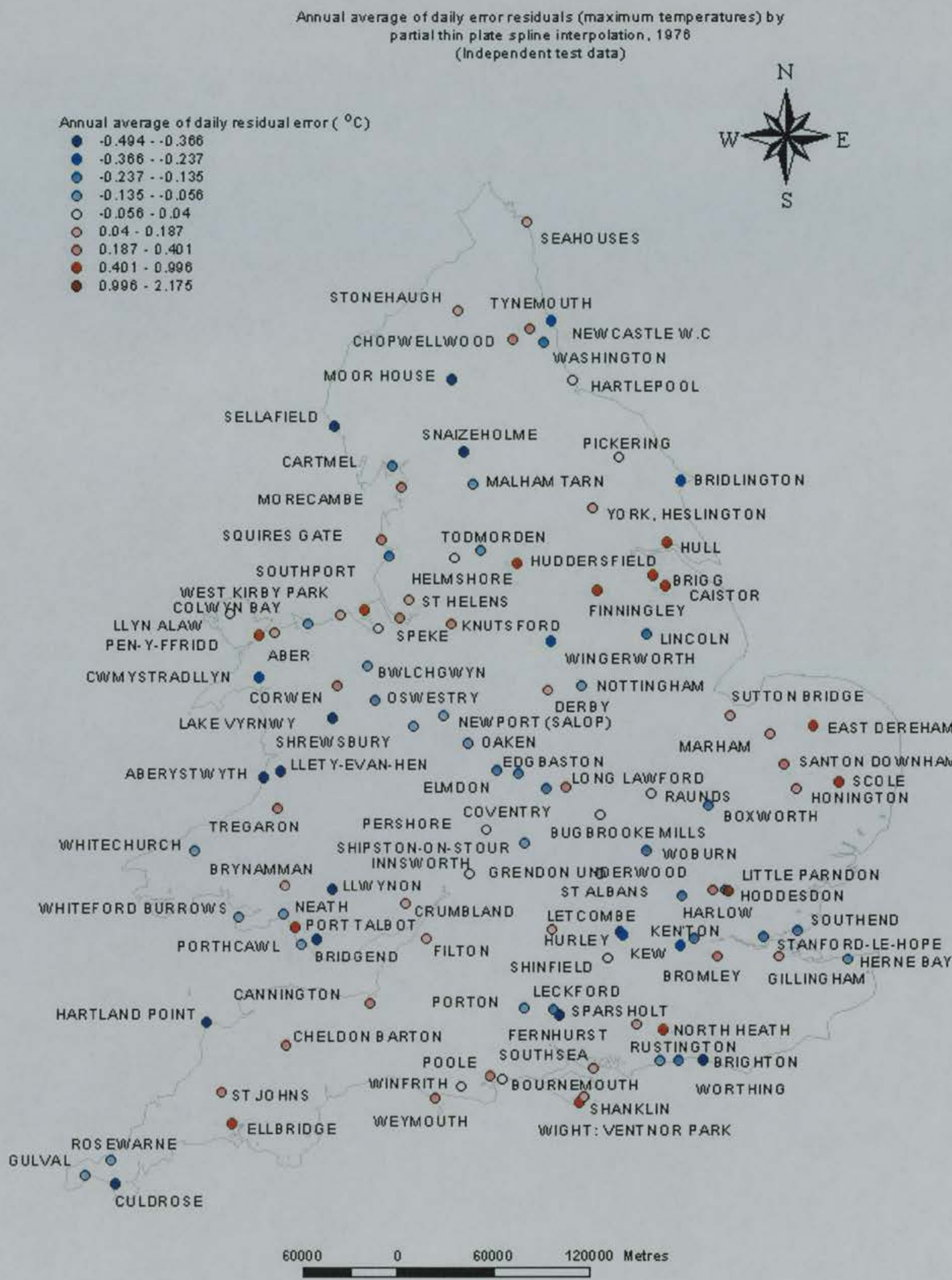


Figure 5-20. Average residual error (annual daily aggregate) by partial thin plate spline interpolation, maximum temperature, 1976

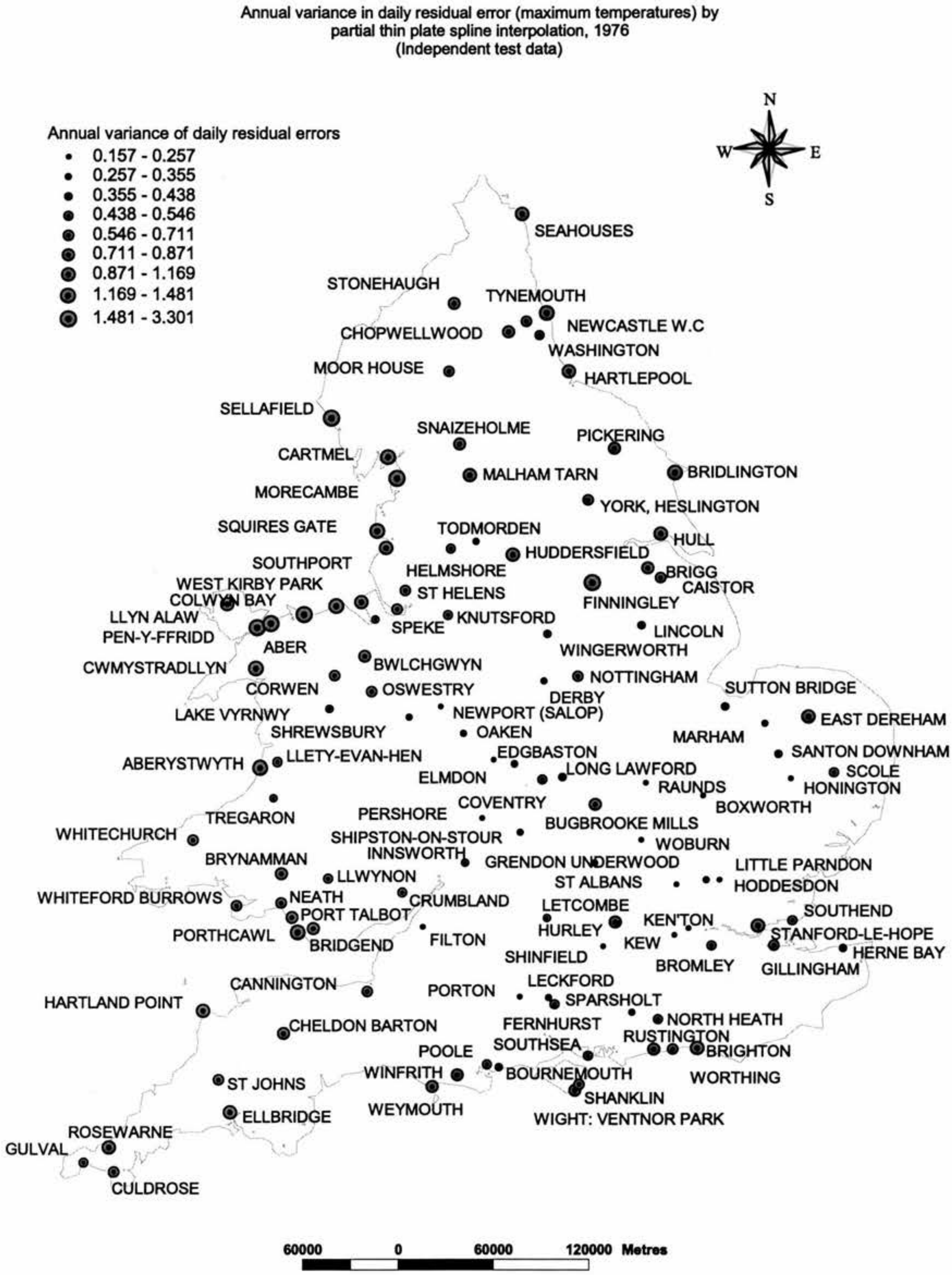


Figure 5-21. Variability (variance) of daily residual, 1976, maximum temperatures interpolated using partial thin plate spline interpolation

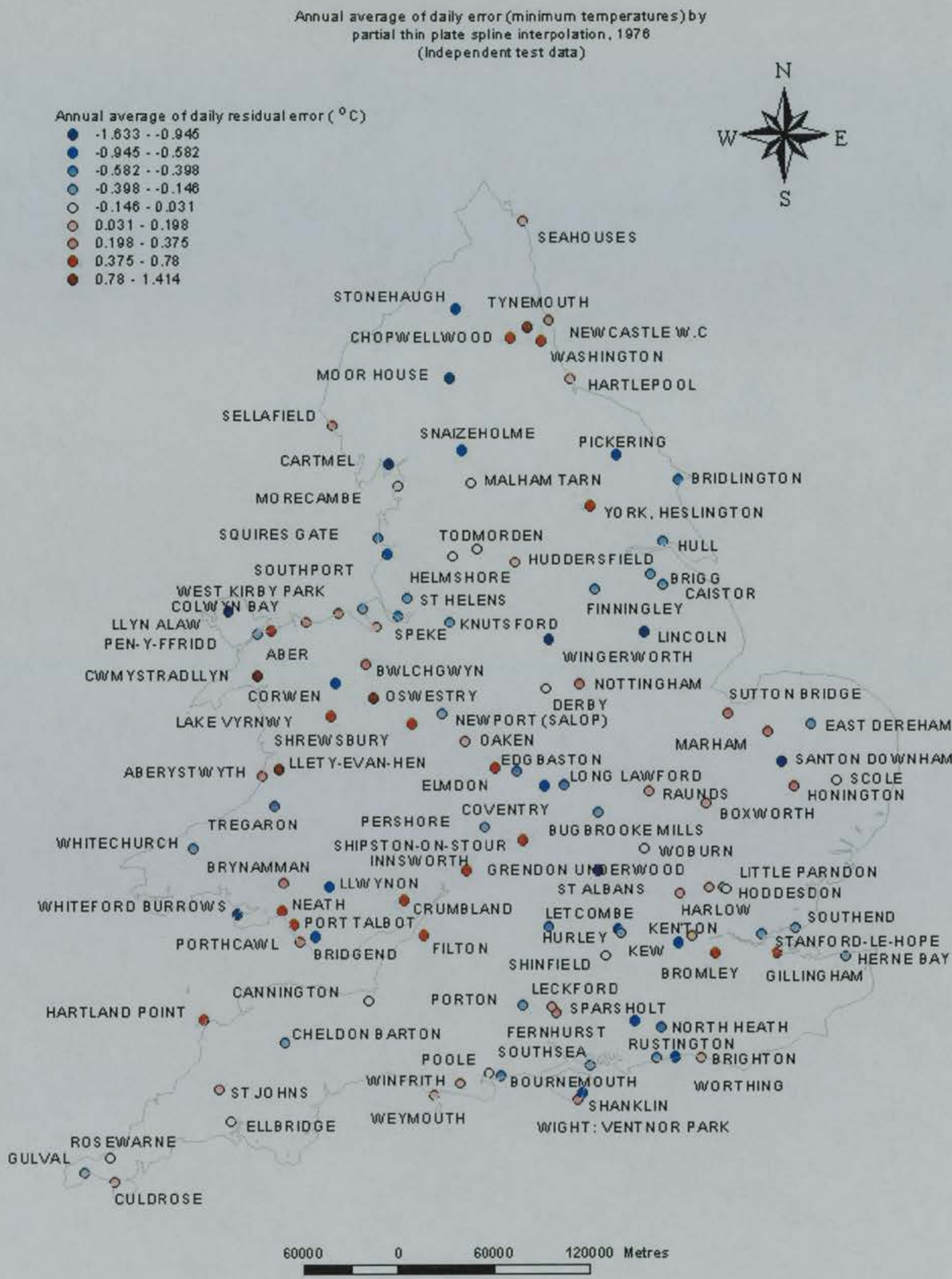


Figure 5-22. Average residual error (annual daily aggregate) by partial thin plate spline interpolation, minimum temperature, 1976

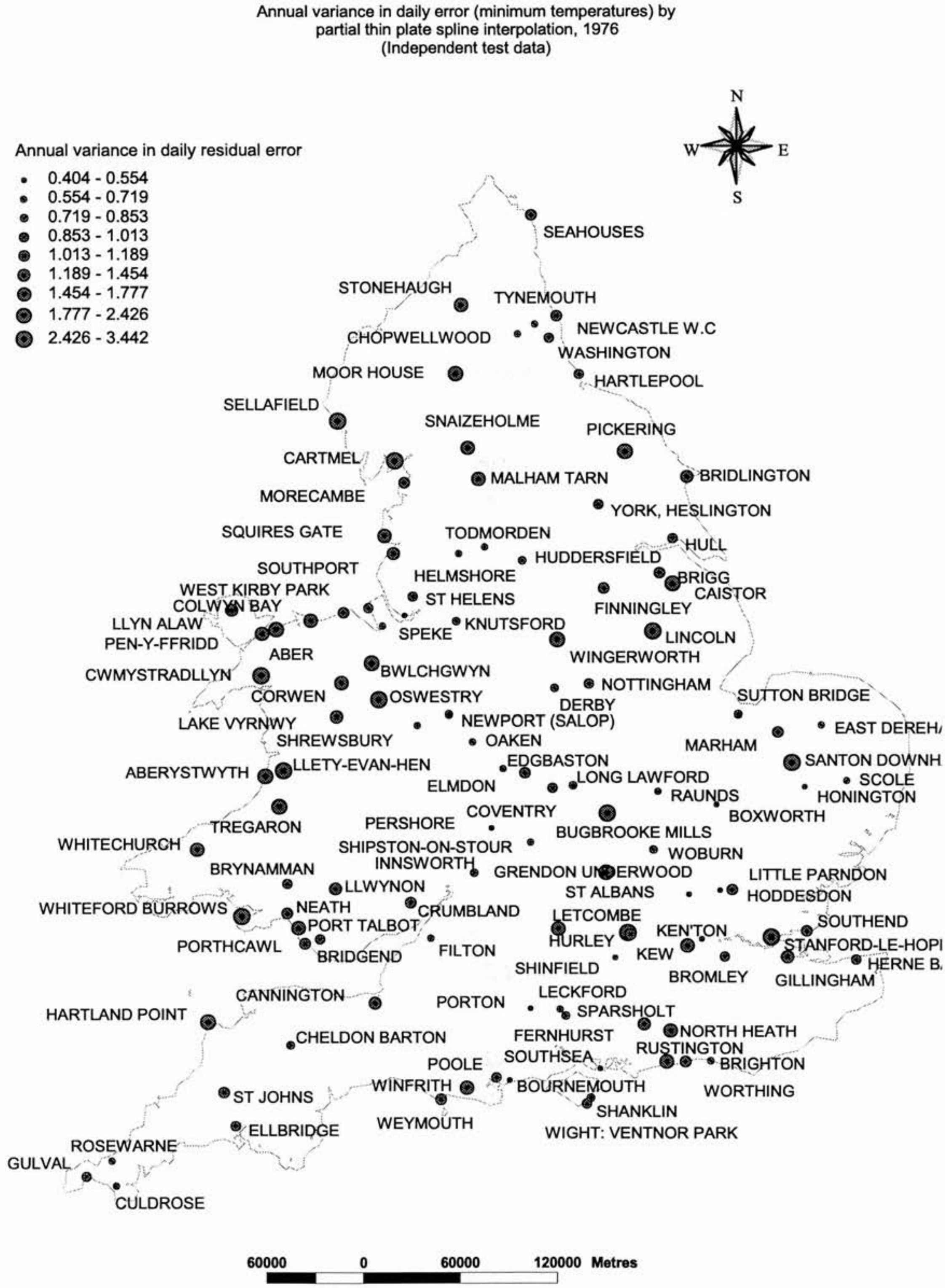


Figure 5-23. Variability (variance) of daily residual, 1976, minimum temperatures interpolated using partial thin plate spline interpolation

5.3.3.2 Accumulated temperature

Moving from temperature analyses to the results of running the accumulated temperature model, residual error distributions (degree days) for the jack-knife cross-validation (c.v.1) and independent test results (independent) across base temperatures 5 °C, 8.5 °C and 10°C are shown within Figure 5-24 below. These plots also indicate the effect of incorporating additional data and re-computing jack-knife cross-validated errors (c.v. 2). This assumes that the extra data might in future be used within the interpolation process rather than retained for accuracy assessment

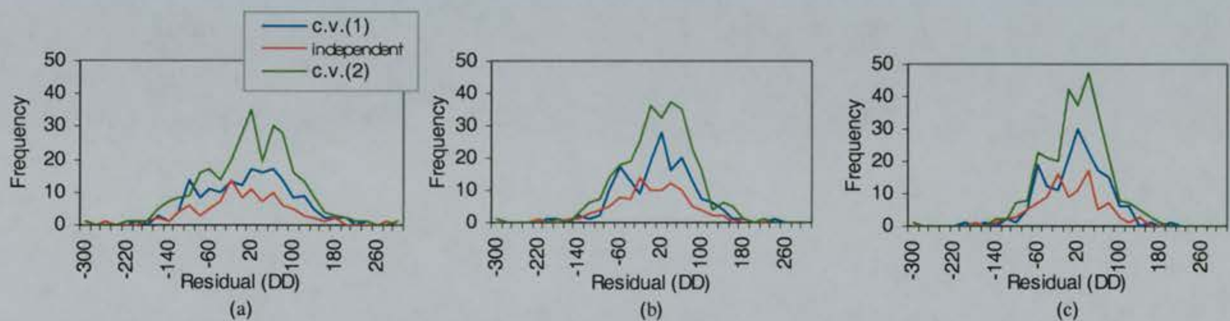


Figure 5-24. Error frequency, cross validated (c.v.) and independent data sets for accumulated temperatures (a) Base 10 °C, (b) Base 8.5 °C and (c) Base 5°C

Table 5-3. Summary table, characteristics of error estimates using additional data as independent test data and for cross-validation, 1976

	Base 5°C		Base 8.5°C		Base 10°C	
	independent	additional c.v.	independent	additional c.v.	independent	additional c.v.
Mean	-5.55	4.80	-9.41	5.26	-6.99	5.54
Standard Error	8.59	4.90	7.00	3.80	6.19	3.29
Median	-3.50	9.00	-9.50	7.00	-4.00	7.00
Mode	54.00	-5.00	-86.00	-1.00	-15.00	8.00
Standard Deviation	85.88	83.37	70.00	64.54	61.86	55.88
Sample Variance	7374.71	6950.52	4899.62	4165.15	3826.62	3122.35
Kurtosis	0.84	0.21	0.26	0.05	0.22	0.15
Skewness	-0.05	-0.13	-0.19	-0.16	-0.19	-0.17
Range	540.00	520.00	389.00	381.00	326.00	336.00
Minimum	-273.00	-235.00	-223.00	-180.00	-195.00	-168.00
Maximum	267.00	285.00	166.00	201.00	131.00	168.00
Sum	-555.00	1386.00	-941.00	1519.00	-699.00	1600.00
Count	100.00	274.00	100.00	274.00	100.00	274.00
Confidence Level(95.0%)	17.04	9.65	13.89	7.47	12.27	6.47

The effect of varied data volumes is apparent within (a)-(c), with peak frequencies in the combined data set (274 data points, Table 5-3) and lowest frequencies within the independent test set (100 data points). Visual inspection suggests a positive bias within the combined cross-validated data (green line) relative to the independent set (red line), confirmed mathematically within Table 5-3 which reveals higher positive extreme residuals in the c-v data relative to the independent data and more conservative 95% error bounds for independent rather than cross-validated samples. In comparison with the findings reported in Section 5.3.1.1 above, additional data reduced the extremes in maximum and minimum residuals, as might be expected. Data were selected according to station reliability and consistency across the years (p84). While a deliberate attempt was made to incorporate stations at extreme elevations where possible within the original selection process in order to minimise extrapolation within the covariate parameterisation process, the balance of independent data is likely to be from the relatively inaccessible (upland) climate network stations rather than synoptic stations. Data from this climate network are often amateur recordings and by their nature are more likely to be prone to higher error.

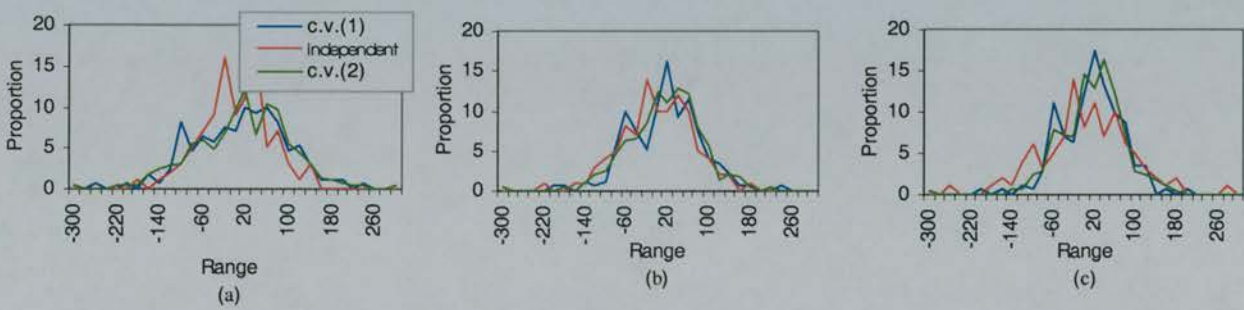


Figure 5-25. Proportional error distribution, cross validated (c.v.) and independent data sets for accumulated temperatures (a) Base 10 °C, (b) Base 8.5 °C and (c) Base 5°C

In order to enhance comparability, the proportional error (%) rather than absolute size of errors at the stations are plotted within Figure 5-25. That is, residual errors (DD) are expressed as a percentage of the 'actual' accumulated temperature computed using meteorological station data at their respective locations. Firstly, this re-scaling allows the more direct visualisation of histograms computed from data sets of differing volume (Table 5-3). Additionally, especially given the spatially predetermined nature of synoptic meteorological data, no two samples of station data are likely to have exactly the same geographical characteristics. High accumulated temperature results are dependent on higher than average temperatures, which from Chapter 4 (Figure 4-17) are known to contain correspondingly high residual errors. Re-scaling is likely to restrict the bias that results from this situation where differences in the representative nature of the two sample sets arises. Comparisons between Figure 5-24 and Figure 5-25 confirm this suggestion that residual size is indeed related to accumulated model result through the significant reduction in difference between the error distributions of the three validation test sets. T-tests show there to be no significant difference (95% confidence) between the means of the three validation results for all three accumulated temperature model runs (Bases 5, 8.5 and 10°C). While a slight negative bias remains within the independent data, Kolmogorov-Smirnov tests revealed these proportional error distributions to be normal with 95% confidence. While the variances of the smaller and complete data configurations used for cross-validation were similar, those between independent and cross-validated data were dissimilar in variance, with direction of the difference dependent on the base temperature selected for the model run.

5.3.4 The computation of 'error surfaces' by interpolating the point error results from jack-knife cross-validation

As outlined within Section 3.3.3.1, a number of researchers advocate the interpolation of cross-validated residuals in order to construct an 'error surface' from interpolation (e.g. New, pers. comm.). Within the climate interpolation literature for example, Robeson and Willmott (1993) interpolate the cross validation errors from a number of interpolation techniques, while Lennon and Turner (1995) interpolate residuals from their monthly temperature interpolation analyses. This section reports on the conundrum posed within Section 3.3.3.1, that *if* the representation of both spatial autocorrelation and underlying process is optimal given the available data in the original model, then a logical working hypothesis is that no identifiable trend or local spatial autocorrelation will be identifiable within the residuals, which are therefore rendered un-interpolatable.

Spatial association is commonly measured using the variogram, as discussed within Chapter 3 and modelled for temperatures within Chapter 4. If local autocorrelation has been captured within the original model successfully, subject to the available data, then no further spatial association (measured by changing semi-variance) should be discernible within the residuals. Figure 5-26 below indeed demonstrates for the accumulated temperature model at bases 5, 8.5 and 10°C that no range may be computed from the empirical variograms of the residual model results. Any remaining spatial autocorrelation therefore exists at distances of less than 20km (minimum lag distance), if at all.

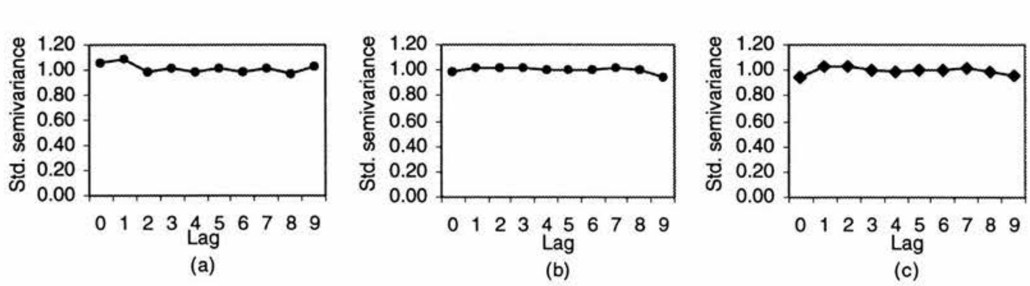


Figure 5-26. Standardised semi-variance of residuals for accumulated temperature, 1976 (a) Base 10°C, (b) Base 8.5°C and (C) Base 5°C

Interpretation of Figure 5-26 suggest that neither large-scale trend nor local association exists within the residuals. This lack of both local and global association makes all four interpolation techniques used within this study (Chapter 4) difficult to justify. The range-less variograms plotted rule out the use of both kriging and 'automated' IDW methods, while exploration of the partial thin plate spline surfaces of the residuals indeed produced surface equations with poor fit beyond the appropriate bounds explained within Figure 3-17. Residual 'surfaces' were therefore computed using high order trends and average inverse distance weighting (i.e. power of 1) over the standard range of 12 data points. The means by which residual surfaces are computed in other work (e.g. Lennon and Turner 1995) are often unclear, although the complexity of the surfaces produced rules out the use of low order trends and suggests that either a spline or a local averaging method has been applied.

The interpolated surfaces for residuals from the accumulated temperature model running over the three base temperatures were spatially similar, and so the residual error surface for the accumulated temperature model with base 8.5°C only is mapped (Figure 5-27). As is immediately evident from

Figure 5-27 neither method of interpolation can create a continuous surface that captures the variability within the model residuals satisfactorily, although on the basis of visual evidence the local method reflects the characteristic pattern better. The apparent lack of a continuous surface within Figure 5-27(b) is in part an artefact of legend scale, caused by the desire to make the two 'error surfaces' directly comparable.

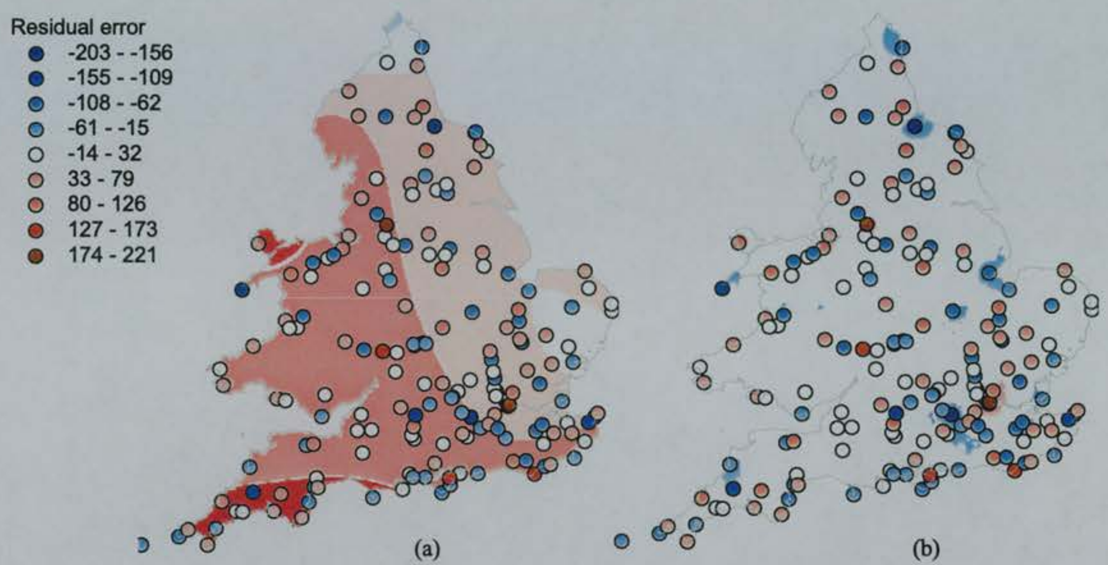


Figure 5-27. Point residuals from the partial thin plate spline interpolation of accumulated temperatures (Base 8.5°C) and their interpolated surfaces by (a) fifth order trend and (b) inverse distance weighting

In constructing Figure 5-27, the standard 174 point data set was used both for the interpolation of temperatures and in the interpolation of the cross-validated residuals, as is the case throughout the thesis. The values of the interpolated accumulated temperatures at the independent set of 120 points used in the previous section could therefore be compared with 'actual' accumulated model results computed on the basis of the known independent meteorological data to provide 'true' residual information. This provided a benchmark against which the interpolated residuals could be assessed quantitatively. Quantitative comparisons between the r.m.s. errors computed using the residual data at the independent sites versus their interpolated estimates at these locations are reported within Table 5-4.

Table 5-4. Independent validation of the residual error surfaces

	r.m.s. error (DD) (IDW)	r.m.s. error (DD) (trend)
acc5	90	151
acc8.5	75	154
acc10	66	148

For both trend surface and inverse distance weighted interpolations, when the difference was computed between the interpolated residual surface and 'actual' figures at points of independent data, the values of the errors were in excess of those of the original modelled results. The implication of these results is that whether one should even attempt to create such a surface at all is a debatable point.

5.3.5 Error propagation and validation: discussion

Errors reported for the biological models are solely those arising as a result of inexact interpolated input data, and assume zero biological model error. The findings show that, as for the temperature results of Chapter 4, the sites with largest and/or most variable errors are located predominantly in remote upland or coastal areas. From an agricultural perspective, this affords comfort. Interestingly however, the relative distribution of error alters with base temperature at locations where the seasonal ability to interpolate temperature is variable. This confirms the complexity of the overall error propagation process, even through a relatively simple model such as that used for accumulated temperature. The importance of the absolute residuals will depend on the application to which the accumulated temperature model is put. The 95% confidence level of 17DD for residual errors in temperatures accumulated over base 5°C for example (Table 5-3) might translate to 17 days in winter where temperatures are close to 5°, or 3 days in summer, of error in the date suggested for control applications. Similar principles apply when considering the question as to whether it is worth applying more sophisticated interpolation techniques to model input temperatures than the trend surfaces of previous work (Figure 5-18). The spline interpolations were consistently found most reliable across all base temperatures, confirming their better adaptability in accounting for seasonal differences in weather pattern than the other methods. Extrapolating to more complex models with multiple thresholds throughout the development cycle, and the more generic use of the software designed for the thesis, this consistency in the performance of the partial thin plate splines (especially over winter months) would appear advantageous. This is particularly the case when considering the extension of the biological applications of this work to future considerations of, for example, insect overwintering. Whether this error is similar throughout the year, or accumulates in a highly variable manner according to season, will be explored in the next chapter. In an applied agricultural context, further estimation of the combined biological and spatial modelling error through the use of independently sited insect trap catches would be needed to provide confirmation of 'fitness for purpose'. Meanwhile, the partial errors computed allow the apportionment of error relating to sparse data inputs alone. This allows the geographical case for an improved focus on input data used for phenological modelling to be explored, in addition to the current emphasis in the biological literature on improvements to the pest models themselves. This issue will be returned to within chapter 7.

Ideally, each phenological surface would be accompanied by an 'error surface' showing where most confidence could be placed in the results. As demonstrated in section 5.3.4, simple techniques commonly advocated within the literature are not sufficient to encompass the many contributing factors to the overall geographical form of error. The review of current strategies for propagating error (Section 2.3.4) indicated a considerable research gap in its quantitative modelling through both space and time. Monte Carlo analysis offers a theoretically pragmatic strategy (Heuvelink, 1999) and Philips & Marks (1996) for example used Monte Carlo techniques to propagate the kriging variance from three input layers through an ecological model. However, given the national extent of this study, together with the 30-year temporal range for analyses and daily input surfaces over each annual period, such an approach would present considerable computational problems. Moreover, the kriging variance (or the equivalent standard error surface from partial thin plate spline, e.g. Hutchinson (In Press)) depends on the spatial configuration of data and not their absolute values. When the variance is propagated, it will not necessarily reflect the spatial pattern of the underlying error surface even if the global statistics are appropriate. The growing suite of conditional simulation techniques (e.g. Deutsch & Journel 1998, Atkinson 1999) provides a number of techniques such as sequential Gaussian simulation and simulations using simulated annealing methods that would provide equally viable and spatially coherent input surfaces for a Monte Carlo analysis (e.g. Mowrer 1997). Investigating these methods for interpolating daily maximum and minimum temperatures, in particular how the guiding topoclimatic variables may best be incorporated and how error within the residuals from regression could also be accounted for in the simulation process would form an interesting study in itself. Differences between jack-knife residuals between base temperatures demonstrate that for this application error is more than simply an issue of data configuration. The ability or otherwise of the topoclimatic variables to account for the effect of topography on underlying weather patterns on different dates and locations also forms an important factor in the propagation of error.

This discussion points to the need for research into more elegant approximations to the space-time propagation of error, a topic also encouraged by others such as Heuvelink (1998). Large volumes of empirical data and simpler rule based biological models would alternatively allow the development of Bayesian network for the production of error surfaces, although as Elmes et al. (1994) outline this would be no trivial task. Meanwhile, the production of fully spatio-temporal error surfaces of phenology or pest risk was considered beyond the scope of this study. Adding weight to this argument was the fact that details of the errors inherent within the biological models themselves were not available for inclusion within such a modelling process: at best, the error surfaces would be partial representations. Additionally, independent phenological validation data at multiple time-steps that would allow the verification of full error surfaces were not available for this work. The point-based error propagation strategy, in contrast to these more complex options, provided a novel and relatively efficient means of establishing the overall bounds to the error in a particular phenological surface *over time*. It also fulfils an important role in allowing the impact of different input data strategies for phenology modelling to be considered, a subject that will be discussed further within chapter 7 (Section 7.2). It also, through the assessment of the overall distribution of the residuals and their spatial configuration, provides a degree of comfort regarding the performance of the modelling system.

To this point in the discussion, the focus has been placed on the use of jack-knife cross-validation to assess the bounds of accuracy of the modelling undertaken for the thesis. While, within the mathematical literature, such methods are well accepted this is less the case within a geographical and particularly so within insect ecology. The comparisons between estimates computed using semi-independent cross-validated and fully independent test data therefore have applied significance. For estimates of daily maximum and minimum temperatures, validation using the independent data show significantly higher mean errors than are computed using jack-knifing. For minima (Figure 5-19(b)), the overall pattern of error throughout the year remains similar between independent and cross-validated tests but residuals within the summer for maxima peak particular strongly in the case of the independent data (Figure 5-19(a)). Visual comparisons of the spatial distributions of error by validation method are similar for both maximum and minimum temperatures, with high residuals associated with coastal areas and extreme elevations in both cases. The interpolations are computed to a resolution of $1km^2$, such that micro-climatic variations that may affect coastal areas are expected. Minimum temperatures in particular are highly variable, especially in relation to differences in local land cover and aspect. Given the scarcity of data relating to individual site locations with which to account for such differences, and the low volumes of test data given the national extent of the study, these visual comparisons provide only a broad guide to the performance of jack-knife cross-validation.

For the results from the runs of the accumulated temperature model, using independent data appears to result in an over-estimation of error within the day-degree summations. The value of the 95% confidence levels for error across the three temperature bases when computed using cross-validation are only about one half of those computed using independent data. Figure 5-25 provides some degree of explanation in this regard. When accumulated temperature residuals are re-scaled in proportion to the 'expected' model result at a site, there *is no significant difference* (95% confidence) between error distributions computed using either independent or cross-validated data. Differences between validation methods may be attributable to the difficulties in selecting test data that is statistically similar to the original set owing to the restricted total number of meteorological station data and the possibility poorer quality or poorer representation of the overall landscape in the independent data.

Cressie (1991, p498) suggests regarding jack-knife cross-validation and other similar sample reuse procedures that '*the interdependencies introduced into a problem, where data are already spatially dependent, make confirmatory techniques questionable*'. Cross-validation in this study however is performed only on the basis data from which the trend has been extracted, within which the large-scale spatial autocorrelation should be minimised. The re-scaled figures for accumulated temperatures suggest that, for this study, cross-validated estimates are not significantly different from those computed using independent data once differences in location have been taken into account. While independent test data are theoretically preferable, the findings suggest that given the high variability of temperatures over England and Wales in conjunction with relatively low volumes of sample data (174 points) jack-knife cross-validation offers a reasonable means of approximating error distribution in both temperature and phenology results. While the generality of this finding over the full range of models used is unresolved, there is no reason to believe that the outcomes from these experiments are unique to the results for accumulated temperature only.

5.4 Chapter summary

- The production of spatial phenologies by means of phenology models driven by interpolated temperature inputs has only been explored on one previous occasion within the literature, and then using trend surface interpolation that was shown within Chapter 4 to be least satisfactory when compared with other interpolation methods;
- Gridded phenologies at a resolution of $1km^2$ were developed both over a national extent (important for pest risk assessment) and for local areas (more relevant to integrated pest management in agricultural regions). This is though to be the first time that such continuous estimates of phenological development have been estimated over a national extent. In Britain as elsewhere, phenologies reporting nationally on a daily or weekly time step have previously been computed only at those points where meteorological inputs are available (e.g. Parker and Turner 1996), or through regional aggregates of these point-based figures (http://www.sp.dk/pl@antinfo);
- The nature of phenological outputs from the three main models linked with the system provided by the research software have been introduced. This framework extends upon on previous work which enabled the production of 'snapshot' spatial phenologies (Régnière 1996). This research allows:
  - the mapping of the date within any given year (1961-90) at which a pest at any given location reaches a specified stage in its development;
  - gridded sequences of phenological emergence in a local area on a daily basis;
  - time-series graphs of pest development to be produced at any $1km^2$ cell, rather than confined to the limited number of locations where meteorological data records are available as previously;
  - spatially referenced jack-knife cross-validated residual error estimates for the spatial phenologies at 174 locations throughout England and Wales.
- These last three capabilities arise as a result of the decision to produce spatial phenologies using interpolated temperature inputs, and are unique to this study.
- The limited number of spatial phenologies previously mapped have related almost exclusively to forest pests such as the gypsy moth in a North American setting, rather than these British-based agricultural pests;
- Residual errors in the spatial phenologies computed using jack-knife cross-validation errors were explored using the accumulated temperature model running over three different base temperatures. The distributions of error from this simple model, which represent the error arising as a result of the interpolation process rather than that attributable as part of the calibration of the biological model itself, showed little bias (<5DD) and only minor skew. It is therefore concluded that the modelling approach neither systematically over or under –predicts accumulated temperature;
- It was found that spatial accuracies within the residuals from the accumulated temperature model

were a compound construction of the errors discussed separately in Chapter 4 for maximum and minimum temperatures. The largest model errors were associated with locations in which the direction of bias in both maximum and minimum temperatures occurred in opposing directions. Differences in error distribution between accumulated temperature models run over different base temperatures highlighted the impact of seasonal variability in input errors at different locations;

- The availability of additional daily maximum and minimum temperature data late within the project cycle allowed a theoretically preferable independent assessment of the temperature results, and also the computation of 'expected' model results and residuals at these points. When differences in representation of the overall landscape within the underlying data sets were taken into account by expressing the residuals in proportion to actual model estimates, no significant differences were found between errors computed by cross-validation and independent station data;
- The legitimacy was explored of the common practice of interpolating residual errors (DD) computed using jack-knife cross-validation using both inverse distance weighting and trend surface analysis. No spatial autocorrelation was measurable within the residuals. Comparisons between residuals computed using independent data and those of the interpolated 'error surfaces' showed that the r.m.s. error associated with the interpolated residuals was greater than that for the original model surfaces themselves. This suggests that, other than mapping the point residuals, the practice of seeking to produce a fully spatial map of residual error should be avoided.

6 Temporal and spatial uncertainties in phenological predictions

6.0 Introduction

This chapter reports on the issue of whether to interpolate the inputs to a phenological model (in this case temperatures) or to first run a phenological model only at meteorological stations and then use interpolation to make a gridded surface of these phenological values, a subject introduced within Chapter 2 (Section 2.4.2). These two routes to creating spatially continuous estimates of phenology (termed spatial phenologies within this work) are illustrated within Figure 6-1. This issue will be considered in some detail here as it has received relatively little attention in the applied field of insect ecology, or within GIScience and environmental modelling as a whole, and the implications of choosing one or another approach have not been thoroughly examined. As previously noted, in this application area the interpolation of model results has been almost 'de-facto' to date (Schaub *et al.* 1995b, Régnière *et al.* 1996). Russo *et al.* (1993) provide a rare exception.

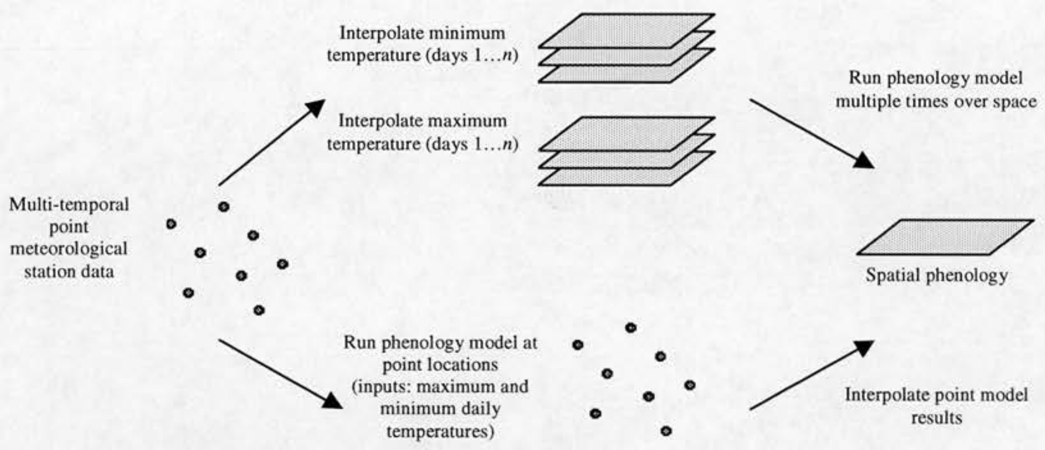


Figure 6-1. Interpolate temperatures (upper path) or phenologies (lower path)?

The two approaches do not necessarily lead to equivalent outputs. Where model inputs (in this case, temperatures) are interpolated, considerable effort needs to be expended to extract accurate and high quality estimates of the input variables driving the phenology models to ensure an appropriate quality is maintained within the estimated spatial phenologies. Considerable scope exists for errors to be introduced or propagated through the processing order, which need to be examined from a geographical perspective when weighing up which is the most appropriate approach.

The method followed to investigate this issue was a focused numerical analysis, coupled with practical observations in order to provoke modellers into considering the broader implications of the two approaches. The aim is to bypass an initial outlay of work high in computational intensity where possible and to assist modellers to weigh up the relative merits of performance versus quality issues in their own research domain. By viewing the implications of the decision to interpolate model outputs rather than inputs in terms of data integrity through space and time, the work complements discussions of error propagation within the geographical literature. Work by Heuvelink (1998) and Arbia *et al.* (1998) among others have progressed our ability to model error propagation within environmental models in space, but the temporal aspects of error propagation have still to be addressed. The importance of tackling this issue may be justified by exposing the potential magnitude of such errors.

The effect of the strategies of either interpolation first or modelling first are explored for all three major phenological model types introduced within Chapter 3 to examine the generality of the extent to which either method performs better than the other. This is necessary because the differing structure of the models (linear, linear within life stages plus thresholds and non-linear within life stages) may also contribute to the relative accuracies within the results.

This chapter concentrates on examining quantitative errors arising within the computed attribute values (phenological outputs), rather than errors in position (e.g. exact location of cells). This is common within other discussions on error in environmental data analysis (e.g. Heuvelink, 1998) and may be justified here because the resulting phenologies are analysed for their general patterns and distributions of risk and are not intended for fine locational decisions at a sub-1km^2 level. Simple metrics are used in contrast to the full spatial error simulation approach suggested by Burrough (1992), in recognition that such simulations in space-time require considerable research in themselves and would inevitably be highly computationally intensive as discussed within Chapter 3. These metrics include considerations of overall point based 'r.m.s.' accuracy, logical errors in the developmental sequence of the insects and the spatial coherence of the interpolated results:

- Overall cross-validated root mean square (r.m.s.) error (Section 6.1.1)
- Logical error (Section 6.2.2);
- Spatial coherence (Section 6.1.3).

Within this Chapter, each model run reported is initiated at the start of a year (1976, 174 stations as per Figure 3-11) with a population of viable, mature adults and the models are run over the full calendar period. The 'best' partial thin plate spline interpolation models from the earlier chapters are used consistently throughout. Error is discussed by means of an analysis of residuals derived using jack-knife cross validation both between and within developmental stages for both interpolation strategies. The research software developed makes possible the intensive calculation of these cross-validated statistics since it is efficient relative to many mainstream GIS, owing to the fact that the process of estimating interpolation functions for each date and meteorological variable is separated from the grid production itself.

Firstly, interpolated maximum and minimum daily temperature data were passed to each pest model to create fully spatial phenologies; secondly the Julian dates output at point locations by each phenology model were interpolated. The cross-validation facility was used to generate the underlying data for construction of the three error metrics listed above, which will be explained in more detail in the following sections. Alternative versions of the metrics may also be computed on the basis of the geographical phenologies produced by the two interpolation strategies for the final two error measures listed.

6.1 Error metrics: methodology

6.1.1 Overall root mean square error

Within Chapter 5, cumulated errors for specific target events (in that case, end-of-year accumulated temperatures in DD) were introduced in both an aggregated and a spatial form. This chapter explores these data further, tracking the accumulation of errors within lifecycle stages as well as between lifecycle changes in the temporal domain in order to investigate the effects of model structure upon the final errors in phenological estimates. Root means square (r.m.s.) errors (computed using the residuals from jack-knife cross-validation) were computed for multiple events through the codling moth and Colorado beetle lifecycles at development intervals of 5%. These figures are used to represent aggregate 'location free' results for the 174-point data set throughout England and Wales. In the case of the accumulated temperature model, runs were made over different base temperatures over time and the model results are presented as the temperature in °C accumulated during the run period ('degree-days'). Additionally, the errors in Julian date on which a set accumulated temperature threshold was passed were computed over a sequence of increasing thresholds. For insect phenologies the errors are reported as Julian dates at which particular points in the insect lifecycle are reached. The jack-knife cross-validation methodology was used to compute differences in dates from the models based either on interpolated temperatures or phenologies (Figure 3-17).

6.1.2 Logical error in insect development sequence

Consideration of logical errors is more commonly made when checking categorical data or database integrity than in the modelling of environmental processes (e.g. Lanter and Veregin, 1992). Indeed, as Veregin (1999) notes, while theoretical topologies for investigating temporal consistency have been developed (Langran 1992), very few of these ideas have actually been applied to investigate errors in the temporal domain. Within the database community, deductive databases have been developed that allow for logical modelling to identify conflict and redundancies (e.g. Paton *et al.* 1996) which could be applied. This metric developed for the thesis addresses the sequencing of natural states in insect development (e.g. adult, egg, larva, pupa). Within a management context it may be necessary to follow the progression of insect development day-by-day at critical times of the year. For biological credibility, the question as to whether the correct biological sequence is preserved during a model run is as important as knowing how accurate are the overall predictions of the date at which an insect is expected to reach a certain stage of development. The issue of logical sequence error only arises in relation to the estimation of phenological dates (model outputs). If interpolations of temperature are first made and the biological model run at each and every pixel, the model will enforce the correct sequence of dates and temporal inconsistencies are not possible if modelling after interpolating. Conversely it is feasible that grid cells remote from actual meteorological stations in an ill-defined interpolation surface, for example estimating an egg target event date, may contain larger (later) date values than the date that may be estimated by a measure designed to ensure subsequent dates for following stages (e.g. larvae).

Focusing on the time domain therefore, measures deigned to identify the logical consistency between the dates at which each defined development threshold was predicted to be reached were computed on the basis of the point cross validation results from the interpolated phenologies. Logical errors within the sequence of interpolated phenological output grids were also mapped at different stages for a small study area to investigate the spatial pattern of the phenomenon. This technique is advocated as a simple form of '*data quality filter*' (Paradis and Beard 1994, Beard and Buttenfield 1999).

6.1.3 Spatial coherence of the interpolated results

The phenology results were also analysed to investigate how the spatial smoothness or fragmentation of the interpolated results (here termed 'spatial coherence') reflected those of the original point model results. This was achieved both using measures of semi-variance on the basis of cross-validated point results at the 174 data points and secondly using Geary statistics computed using the output phenology grids.

Experimental variograms for both the estimates of accumulated temperature and Julian dates at the withheld points for the two interpolation-modelling approaches, together with 'actual' results computed using the known 174 meteorological station data, were constructed. The unit of lag used for computation was 20km since 18km was the average nearest neighbour distance between the original meteorological data sites. A measure of the adequacy of the gridded results was taken to be their similarity or difference in spatial-autocorrelation. This was determined on the basis of how closely the semi-variograms of the data values from the two interpolation methodologies, as estimated using cross-validation, matched the variogram modelled with known station data. Where the interpolation-modelling technique over smoothes at-a-site model results, the variogram range of the modelled data might be expected to exceed that of the actual station data, and vice versa. In the worst possible case no range will be detected in the interpolated results but would be distinguishable in the 'actual' variogram for the station data. If found, this would imply that simple averaging techniques might perform as well in these circumstances as more sophisticated interpolation algorithms.

In addition to the variogram modelling, based upon point data, Geary autocorrelation statistics (Table 6-1) were computed for the phenology grids computed using the two interpolation approaches. The Geary index was chosen in preference to the more common Moran index owing to the taxonomic similarity between variogram analyses and Geary statistics: both methods depend on the squared differences between values. The Geary index provides a measure of covariance used to test the similarity of near neighbours: in this case, over a grid of dates for reaching a given phenological stage (Table 6-1). This is computed here as a global measure, based on simultaneous measurements throughout the surface and interpreted as shown in Table 6-2. By analogy, the variogram (also a global measure) can also be thought to represent the spatial structure in the phenology results and provides a measure of how the point estimates of phenology from cross-validation retain or lose similarity over increasing separations.

Table 6-1. Computation of Geary index, after Getis and Ord (1992)

n the total number of cells in a grid;

i, j any two adjacent cells;

z the value of the attribute of cell i;

c_{ij} the similarity of i's and j's attributes;

w_{ij} the similarity of i's and j's locations, w_{ij} =1 if the cells I and j are directly adjacent (4 - adjacent) and 0 otherwise;

σ^2 the sample variance, where z_m is the mean cell value for the grid.

$$\sum (z_i - z_m)^2 /(n-1$$

Where $$c = \sum\sum w_{ij}c_{ij} /(2(\sum\sum w_{ij})(\sum (z_i - z_m)^2)/(n-1))$$

$$\sum\sum\sum\sum w_{ij} = 4*n$$

Table 6-2. Interpretation of Geary statistic (After Getis and Ord 1992)

Geary C	Interpretation
C < 0	Similar, regionalised, smooth clustered
C = 0	Independent, uncorrelated, random
C > 0	Dissimilar, contrasting, checkerboard

6.2 Error metrics: results

Results for the three error metrics described above are discussed in turn.

6.2.1 Overall root mean square error

Intuition tells us that errors associated with uncertain daily input values will accumulate through a yearly model run. It is therefore not surprising to find, as Figure 6-2(a) shows, that cross-validation errors are lower for runs over higher base temperatures. The non-linear propagation of errors in the accumulated temperature model is indicated by the sharp rise in error using the less accurate Voronoi method of interpolating daily maximum and minimum temperature, as opposed to partial thin plate splines. Current applied entomological practice for interpolating temperatures in simple entomological models is to apply Voronoi polygons around meteorological sites. The accuracy of results using this method is shown in Figure 6-2 for reference. Because of the compounding effect of daily errors over the period, even small differences in accuracy gained when interpolating daily inputs are worth striving for. In this study, considerable care has been taken with the selection of covariates to guide the splining process, with an annual average error in daily maximum temperature of 0.80°C degrees and of 1.14°C for daily minima. Whilst these findings reinforce the need to choose an accurate interpolator, the issue of whether to apply the interpolation to the input temperatures or output phenologies also needs consideration.

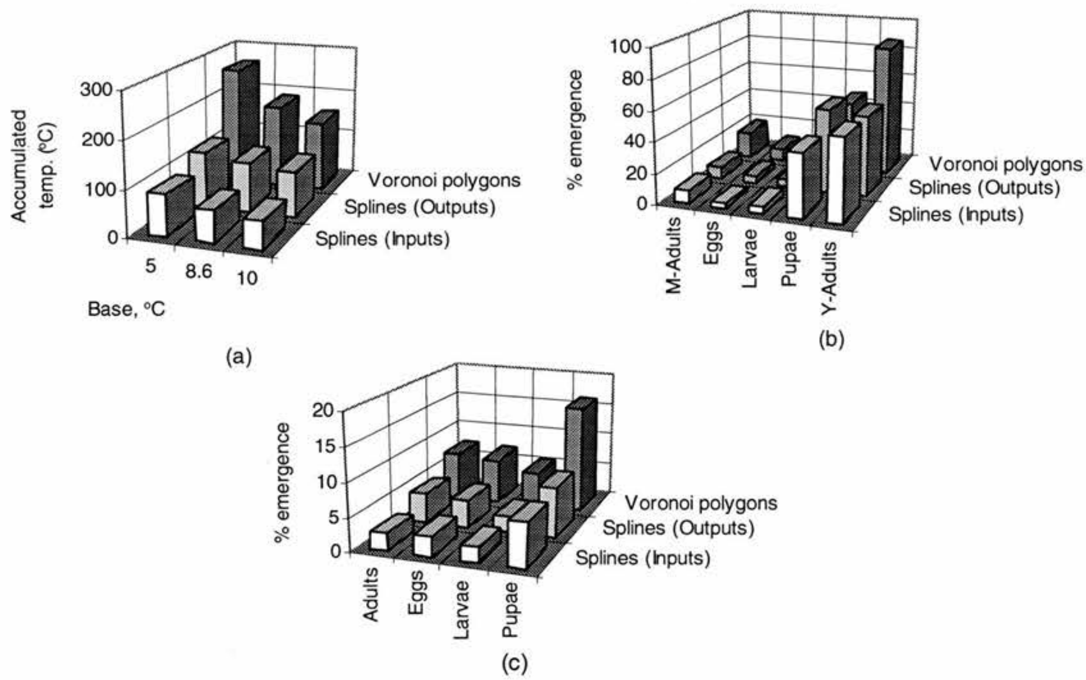


Figure 6-2. Cross-validated error in (a) accumulated temperature results by base temperature, (b) Colorado beetle by development stage and (c) codling moth by development stage (50% emergence), with interpolation approach

In relative terms, for accumulated temperature (Figure 6-2(a)), Colorado beetle (Figure 6-2(b)) and codling moth (Figure 6-2(c)) the difference in terms of the cross-validated point based measure of accuracy at the withheld points between splining the input temperatures or output point phenologies is slight. For accumulated temperature (DD) this difference is approximately 30DD per annum for each base temperature modelled, while in terms of the date at which the phenological stages are estimated to be reached, for the codling moth the average is $\pm$ 3 days.

Considering the results for codling moth further (Figure 6-2(c)) the effect of the time-dependent structure of this model causes the spatial error as measured by the cross validation statistics of Julian dates to fall during the larval stage relative to the preceding egg phase. To interpret this graph, reference to Figure 3-6 (p 76) is needed. Since the rate of development of the larval stage is slower than that for eggs, the model is less temperature sensitive during that phase and accuracies are expected to be lower as a result. The chances of predicting a particular stage of emergence in the insect's lifecycle correctly within this stage on any one day are correspondingly high. Using these point statistics alone as the measure of accuracy, the decision to interpolate model inputs or outputs will depend on the operational significance of the error bands and the variance of the individual point error values. In the context of this subject area, where the efficacy of a chemical or biological application deteriorates rapidly then even small differences may be important. Overall however, the benefit of interpolating phenologies relative to interpolating temperatures may seem slim from the perspective of these r.m.s. point accuracies in comparison to the more influential effect of interpolator choice.

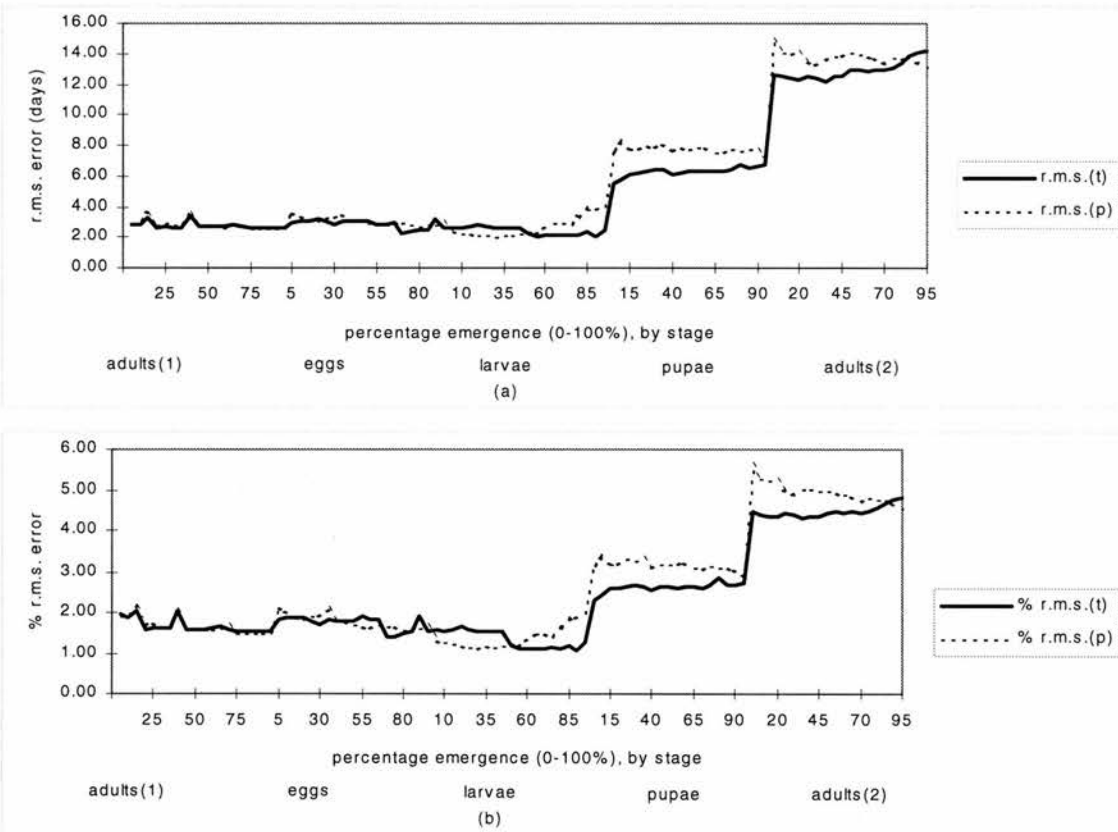
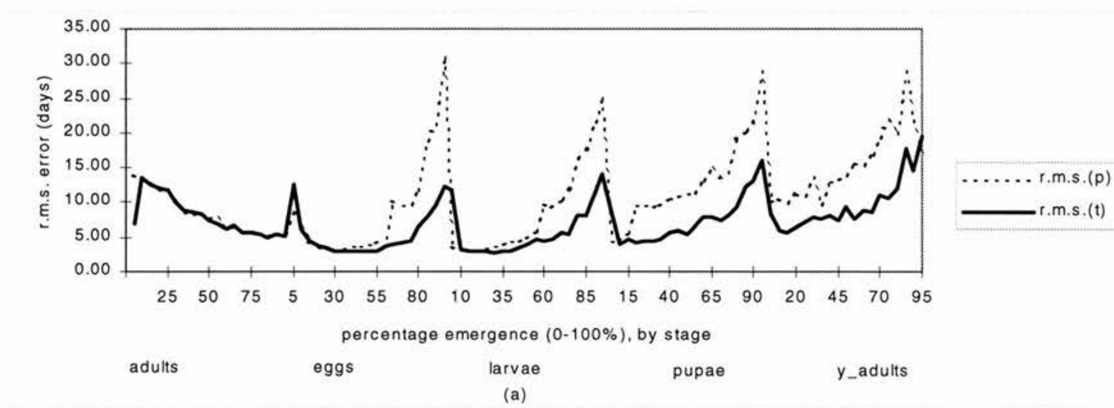


Figure 6-3. Cross-validated r.m.s. error (days) according to the target stage and emergence percentage set for codling moth over England and Wales, 1976: (a) absolute error and (b) percentage error. (r.m.s. (t) - root mean square error when underlying temperatures were interpolated, r.m.s.(p) - root mean square error when phenology results were interpolated)

The figures presented within Figure 6-2 were in fact only computed for particular target events within the pests' lifecycles (e.g. date of 50% emergence, larval stage), and therefore present snapshots of the manner in which error propagates through the models over time. Thus the degree to which error in Julian date varies *within* the lifecycle may not be obtained from Figure 6-2. Just as the focus within Chapter 5 was placed upon the spatial variation in r.m.s. errors (in that case, for accumulated temperatures, DD), Figure 6-3 to Figure 6-5 explore the degree to which temporal fluctuations occur. These are thought to depend considerably on model structure, but such analyses have not previously been considered. Both the absolute and relative errors over the lifecycle are of interest, the former in an applied biological sense and the latter in terms of understanding the propagation of error. It might be hypothesised for example that relative percentage errors (residuals, and therefore r.m.s. errors as a proportion of the actual Julian date or DD values) may accumulate more linearly over time when interpolating temperatures to a greater extent than when interpolating phenologies owing to the small but incremental effect of errors in the interpolated temperatures.

The graphs of Figure 6-3 and Figure 6-4 portray the r.m.s. error measured in days (y-axis), where the x-axis represents the percentage development (emergence) within a particular stage. In the case of Figure 6-5, the x-axis represents increments in threshold accumulated temperature (DD). Time increases from left to right within the plots, but not necessarily linearly since the time taken to complete development through 100% of any one stage may be different according to development rates and the underlying temperatures themselves.



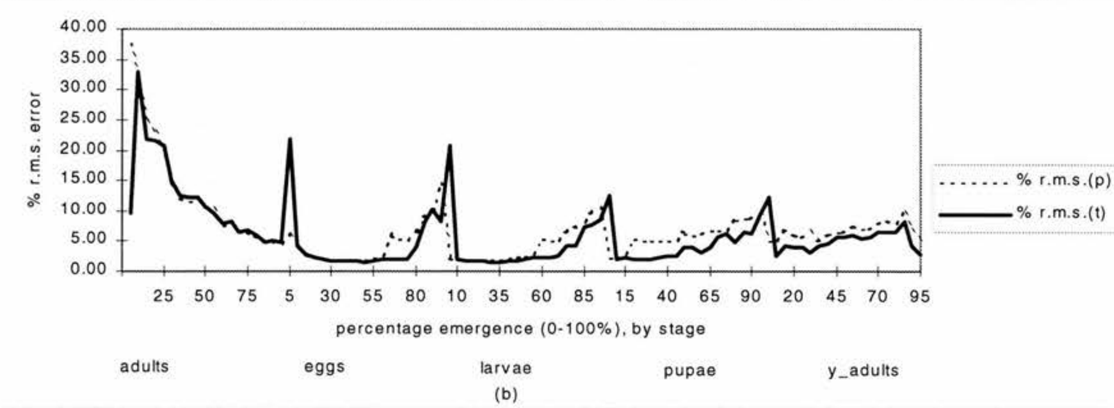


Figure 6-4. Cross-validated r.m.s. error (days) according to the target stage and emergence percentage set for Colorado beetle over England and Wales, 1976: (a) absolute error and (b) percentage error. (r.m.s. (t) - root mean square error when underlying temperatures were interpolated, r.m.s.(p) - root mean square error when phenology results were interpolated)

In the case of the codling moth, error and percentage error in Julian date relative to the actual value over time at the 174 data points have similar profiles. Both increase steadily over time to the pupal stage and then stabilise (Figure 6-3(a) and (b)). During the early phases of the model run (which begins with maturing adults), little difference may be detected between the two interpolation methodologies. During mid-cycle, mid-way through the larval stage (critical for the successful management of this pest), this situation reverses with an approximately 2 day average benefit over the remainder of the cycle provided when interpolating temperatures. In a pest management context this difference may be important, but for PRA assessments this degree of improvement does not confer any particular advantage.

Differences in the error profile between the codling moth and Colorado beetle models are considerable. Towards the beginning/end of each stage, the error curve rises sharply in the case of Colorado beetle (Figure 6-4(a) and (b)). Conditions for transfer of a pest between lifecycle stages depend on a number of abrupt thresholds, for example in accumulated temperature, in the Colorado beetle model (Appendix 6). This compares with the more gentle sigmoidal transition between development phases seen in the case of the codling moth above, and this difference in model structure is a contributing explanatory factor. The significance of these differences in relation to model application will depend on the particular nature of the biological target. One inference may be for example that, where a chemical or biological action is required during an early instar (lifecycle stages may be divided into smaller units, known as instars), or close tracking of the end of a stage is required as in the case of an outbreak of a non-indigenous pest, then errors might be less and results more reliable when using a sigmoidal type of pest phenology model, if available. The finding also suggests that the testing of the accuracy of phenology surfaces should not necessarily be based solely on 'one-off' events during an insect's life-cycle.

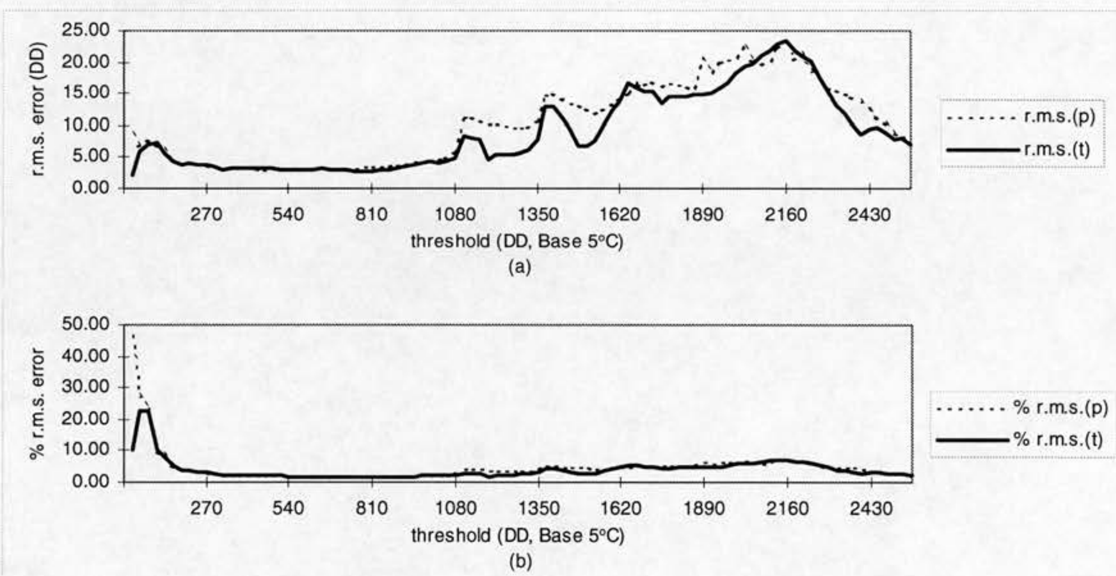


Figure 6-5. Cross-validated r.m.s. error (DD) according to the target threshold for accumulated temperature (Base 5°C) over England and Wales, 1976: (a) absolute error and (b) percentage error. (r.m.s. (t) - root mean square error when underlying temperatures were interpolated, r.m.s.(p) - root mean square error when degree-day results were interpolated)

The benefits of investigating both actual and relative differences in errors arising as a result of the two interpolation strategies are more clearly demonstrated within Figure 6-4(b) than Figure 6-3(b). In terms of absolute error, levels might be hypothesised to rise throughout the insect development cycle when interpolating temperatures before modelling phenologies since errors will accumulate on a daily basis. Equally, since error when interpolating in general increases or decrease in line with the magnitude of the value being interpolated (as shown for temperatures, Figure 4-17, p149), absolute errors when interpolating phenology results may also increase through the lifecycle owing to the 'increase' in date with time. The ease of interpolation for a particular stage, in either case, is better reflected within the relative percentage plots. For Colorado beetle for example (Figure 6-4(b)) in relative terms the predominant direction of change in error throughout the lifecycle is downwards. It appears that the underlying rate of development (Figure 3-4) has a considerable influence on error.

As the proportional error plot for the accumulated temperature model (Figure 6-5(b)) shows, the effect of threshold structure of the model on the errors in date on which a threshold is reached is similarly seen in the sharp gradients at the beginning and, to a lesser extent, end of the run. Once temperatures at all locations over the landscape of England and Wales consistently exceed (or fall below) the 5°C base, the r.m.s. error (in days) stabilises to approximately 5.

6.2.2 Logical errors in time sequencing

The proportion of landscape adversely affected by logical error in the chronological sequences of the various stages of pest development is dependent on whether the results from the phenology model have been 'adjusted' for calendar date (Sections 3.3.2 p115) prior to interpolation to a grid. This may be assessed either on the basis of point cross-validation estimates at the 174 meteorological sites, or across the overall landscape through comparison of the gridded phenological dates for emergence. Without the standard correction applied within this thesis, for Colorado beetle the larval stage was found to predate that of the egg stage in 13% of all cases, and pupae to predate larvae in 22% of cases on the basis of point cross-validation results. Overall, one might infer that for Colorado beetle up to 24% of the England and Wales study area was affected by such errors in 1976, since the location of errors for individual stages does not necessarily coincide. Looking rather at sequencing errors within the gridded phenologies over England and Wales (Figure 6-6(c)), these point-based figures appear to be under-estimates.

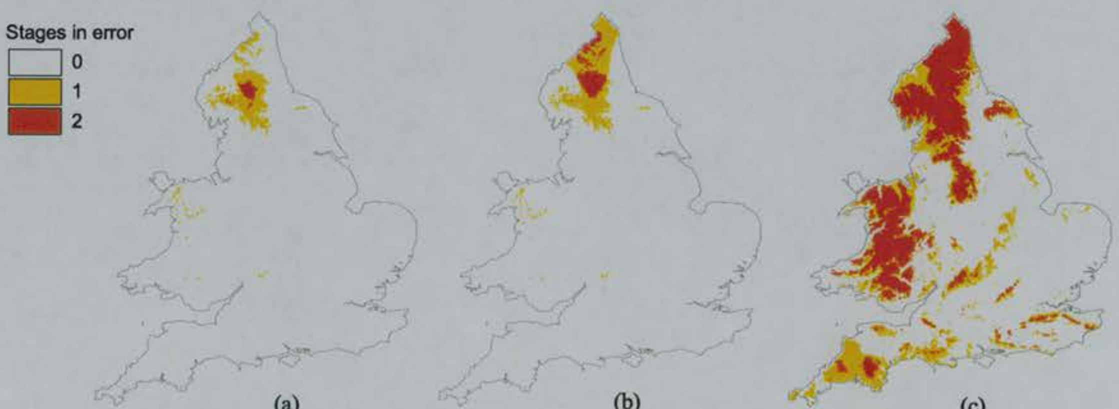
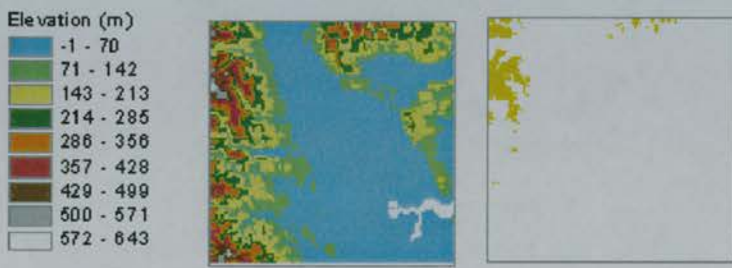


Figure 6-6. Logical errors throughout England and Wales (a) codling moth (adjusted dates), (b) codling moth (unadjusted dates) and (c) Colorado beetle (adjusted dates). (Yellow, one stage affected and red two stages affected by local error)

Overall 37% of the land surface was affected when interpolating actual rather than adjusted phenology dates, of which 21% of the surface area is affected by sequencing errors in two stages. For adjusted interpolations however, the problem is restricted (approx. 3%) to upland areas. In the case of codling moth, both the adjusted and unadjusted interpolated surfaces (Figure 6-6(a) and (b) respectively) still contain logical errors that support the unlikely biological hypothesis that eggs are laid before adults emerge from over-wintering.



(a) (b)

Figure 6-7. Vale of York. (a) Elevation and (b) Locations of logical error (adjusted dates), codling moth, 1976

(a) (b) (c)

Figure 6-8. Logical error, Colorado beetle (a) combined stages (b) young adults and (c) pupae, Vale of York 1976

The spatial locations of these erroneous sequences by stage are mapped in greater detail for the codling moth (Figure 6-7) and Colorado beetle (Figure 6-8) within 100km^2 in the Vale of York area. These maps reveal a strong tendency for errors in the logical sequence over time to occur at relatively high altitudes, where interpolations are relatively poorly estimated owing to the sparseness in the underlying distribution of UK meteorological sites in upland areas. These areas are also ones where environmental gradients, for example of temperatures, are altering rapidly over short distances as shown in the north eastern corner of the Vale of York map.

6.2.3 Spatial coherence

The spatial correlation within the phenologies produced by the two methodologies as measured using the cross-validated estimates may be compared with the degree of correlation found between the original data locations. This comparison is made using the experimental variograms computed for the two spatial phenologies, comparing their form to a variogram built using the actual station data. Figures 6-9, 6-10 and 6-11 portray the standardised omni-directional semi-variance of phenologies for the different methods for various stages in the insect lifecycle. The lag used for computation is 20km, with 18km being the average nearest neighbour distance between the sites of the actual meteorological data.

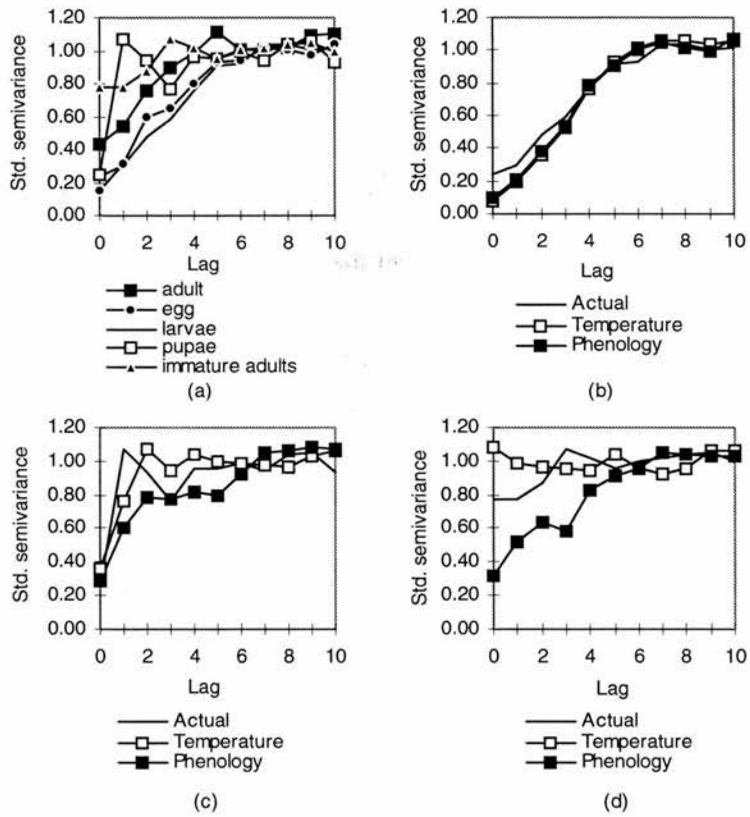


Figure 6-9. Experimental variograms for results of the Colorado beetle phenology model (dates of emergence) using (a) actual data by stage, and cross validated point estimates for (b) larvae, (c) pupae and (d) immature adults from the two interpolation-modelling procedures with the equivalent model run made using 'actual' data included for comparison

Experimental semi-variograms for the Colorado beetle displayed the greatest degree of spatial variability as the biological sequence progresses through time. At the early larval stage, little difference between techniques is seen ((Figure 6-9(b)): either the interpolation of model inputs (temperature) or outputs (phenology) is warranted on this basis. However, beyond the pupal stage (e.g. immature adults, Figure 6-9(d)), the variogram created using interpolated phenologies suggest that spatial association occurs in results at distances of up to 140km. In contrast, those calculated using either known inputs (temperatures at meteorological sites) or interpolated temperatures suggest that little spatial auto-correlation is discernible. This implies that, if present, spatial association will be highly localised to within 20km or under. Under such circumstances, surfaces for immature adults of the Colorado beetle created by interpolating the model outputs (phenological dates) will appear grossly over-smoothed in comparison to the actual data. This suggests that the common approach of interpolating phenologies can provide a false visual impression in comparison with the actual patterns in date. Variograms computed using 'actual' data for each development stage in turn (Figure 6-9(a)) demonstrate an expected fragmentation of the phenological surfaces of dates as the growing season progresses, shown as decreasing ranges. This may arise in part as a result of variation in the underlying distribution of weather patterns between localities on a day to day basis.

As for the modelling of Colorado beetle phenology, interpolating input temperatures for a 5°C base threshold model also resulted in a closer match to the 'actual' accumulated temperature surface as shown in the experimental variograms of Figure 6-9. However, the overall degree of fragmentation represented relative to the results for the Colorado beetle model was considerably lower. In the case of the codling moth (Figure 6-11) there is surprisingly little reduction in spatial fragmentation of the images, which may be a reflection of the more consistent development rates between insect stages used within the PEST-MAN model.

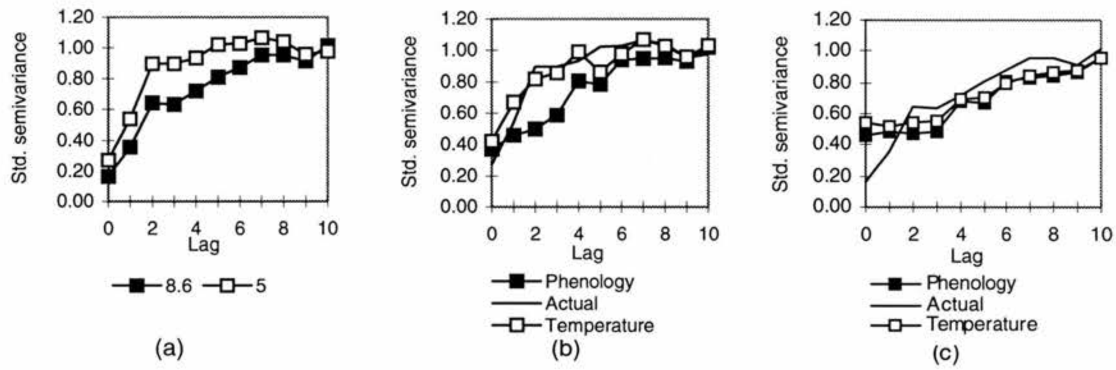


Figure 6-10. Experimental variograms for results of accumulated temperature model using (a) actual data by base temperature, and cross validated point estimates for (b) Base 5°C and (c) Base 8.6°C from the two interpolation-modelling procedures in comparison with model runs made using 'actual' data

Over short model runs, the quicker approach of interpolating model outputs appears to give adequate results of spatial phenology. However, as time progresses, the variance within the phenological Julian date and degree-day surface estimates increases. Interpolating model outputs may become inappropriate in comparison to the safer but more time consuming technique of interpolating temperature inputs. Generally, interpolating input data (temperatures) will produce results that more closely match the spatial structure of results computed using the input meteorological station data. This may be because the spatial autocorrelation of daily maximum and minimum temperatures will stay relatively constant and measurable throughout the season.

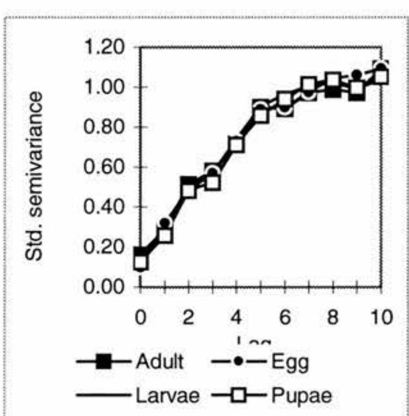


Figure 6-11. Experimental variogram for codling moth model run using 'actual' data

Spatial coherence has been computed so far using the cross-validated point model estimates. Whilst this provides a test of the two interpolated surfaces in comparison with actual data, grids of the spatial phenologies may also be assessed for their spatial coherence. Table 6-3 to Table 6-5 below show the overall coherence of the resultant gridded phenological landscapes in terms of their global Geary statistics.

These figures reflect the general patterns revealed in the variogram analysis with the interpolated temperature based phenology grids (temperature) showing a higher degree of fragmentation than those computed by interpolating date-adjusted phenology results (phenology). For Colorado beetle for example, Geary's c index is 0.271 for dates of emergence of pupae when computed using interpolated temperatures, but only 0.016 when computed on the basis of grids constructed using interpolated phenology. The level of fragmentation increases with life stage, to for example 0.271 for temperature based grids of Colorado beetle pupae from 0.028 for the initial mature adults (Table 6-3). A possible explanation for the comparatively low spatial cohesion in the phenology based grids for pupae and young adults may be patches of consistent zero development occurring in northern or upland areas. These areas will be visualised within Figure 7-3 as a component of the discussion on geographical phenologies for PRA.

Table 6-3. Geary spatial autocorrelation indices of gridded results for England and Wales, by stage of Colorado beetle development, 1976

	Mature adults	Eggs	Larvae	Pupae	Young adults
Temperature	0.028	0.066	0.145	0.271	0.123
Phenology	0.024	0.013	0.016	0.016	0.017

Table 6-4. Geary spatial autocorrelation indices of gridded results for England and Wales, by stage of codling moth development, 1976

	Adults	Eggs	Larvae	Pupae
Temperature	0.013	0.016	0.027	0.031
Phenology	0.011	0.013	0.009	0.014

Table 6-5. Geary spatial autocorrelation indices of gridded results for England and Wales, by accumulated temperatures over different base temperatures, 1976

	5°C	8°C	10°C
Temperature	0.015	0.013	0.011
Accumulated temperature	0.017	0.015	0.013

Changes in spatial autocorrelation by method and stage of development are particularly noticeable for Colorado beetle, but grids also become increasingly fragmented as the model run progresses when temperatures are interpolated as model inputs (Table 6-4, temperature) for codling moth to a lesser degree. Fragmentation in the output grids for accumulated temperatures (DD) increases as base temperatures (°C) decrease, but only to a small degree (Table 6-5). Overall however, the differences in the Geary C statistic for accumulated temperature in particular are slim in comparison with the autocorrelation at increasingly shorter lags observed within the variogram analyses of Figure 6-9 identifiable from models run used actual data at the 174 sample points.

6.3 Discussion

Numerical analysis of the spatial phenology surfaces created by either interpolating temperatures or by interpolating phenologies confirms the importance of considering carefully whether to interpolate the inputs to or outputs from the phenology models. The resulting grids of spatial phenology from the two techniques, while sometimes similar, are not identical and the metrics reflect alternative perspectives on these differences. For example, the r.m.s. point accuracy metric reports similar results obtained by modelling inputs and outputs but the logical errors computed may reveal considerable differences according to pest or stage of development.

The three metrics explored were computed on the basis of two different output types, point based results from cross-validation and gridded outputs. Intimations regarding r.m.s. error, logical errors and spatial coherence may however all be obtained on the basis of the point-based results alone for a more compact analysis in an applied setting. While jack-knife cross-validation was used in this study to construct the overall distribution of errors within the interpolated surfaces, the point-based analyses presented could equally be used to explore residuals from independent sample data. In this way, metrics computed using actual sample data could be compared against those for independent test data to identify the basic adequacy of interpolating model outputs for a particular task. Only if problems were identified would more computationally intensive analyses need to be considered. The results suggest that the more complex the modelling task, or the longer the model run, the greater the advantages of interpolating model input data provided that the input variables are well interpolated.

The results obtained using the logical sequencing metric identified errors affecting significant areas and at important times for pest control (IPM). This provides only a relative, rather than absolute, measure of error however. For the user seeking to model geographical phenologies in an IPM context, the need for precise timings for control and daily sequences of output suggests that the use of all three metrics together may be particularly important. For the modeller requiring a single output, for example an end-of-year position as part of a PRA logical error is unlikely to present a difficulty and the overall r.m.s. error alone may provide sufficient comfort.

Additionally, levels of spatial fragmentation in the Colorado beetle results (Figure 6-2) have implications for model runs over periods covering several months or several stages of development. If the biological model contains abrupt thresholds, such as used here for Colorado beetle model (Section p 73), then the technique of interpolating input data is more likely to produce a spatial phenology map with similar spatial structure to that suggested by the actual inputs. The literature suggests that issues relating to spatial coherence in particular may be more critical when modelling insect populations rather than phenologies as in this case, given the relatively wide variety of factors affecting insect numbers, and that interpolating populations from a limited number of points at a landscape level may be inappropriate.

Using all three metrics together, rather than the more traditional use of the aggregate r.m.s. measure alone, provides a more rounded view of the spatio-temporal ramifications of the question posed. Propagation of error throughout the model run also indicates that, even within a certain stage, errors are not consistent: accurately predicting the date at which an insect moves between stages poses considerable difficulties (Figure 6-3, Figure 6-4), especially for the threshold based model used for Colorado beetle. Few other studies in a GIS context have explicitly included this temporal element, although Mitásová *et al.* (1995) report cross-validated error as glyphs on time referenced display. This provides a snapshot of error changes over time, with a primary focus on the spatial distribution of errors rather than emphasising reliability over time. The results from this chapter also suggest that error in estimating a target date does not necessarily increase over time, as expected: error propagation is a complex, non-linear function of input accuracies, development rates and the rate of change in the input variables themselves. The findings also point to the importance of considering logical errors within environmental databases, especially as the kind of error propagation revealed here has not been considered previously.

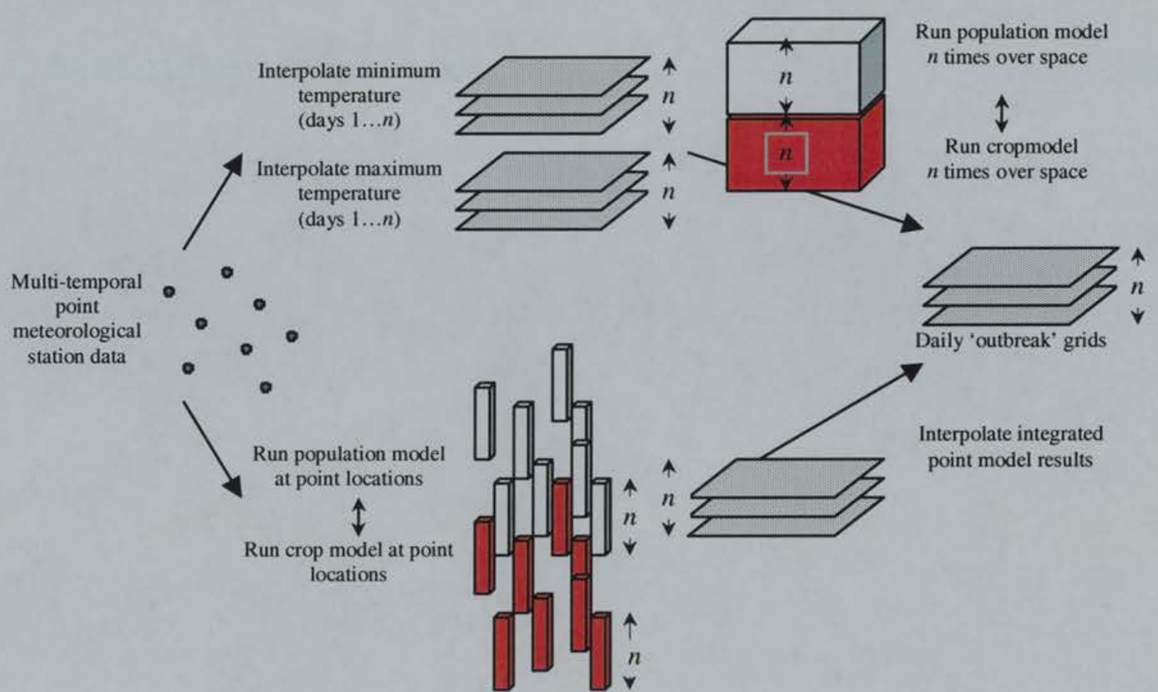


Figure 6-12. Integrated modelling, with a crop model included (additional computational overhead relative to this study in red).

The overall wisdom of considering the interpolation of model inputs rather than model outputs may also be considered in the light of this practical experience. In this case study, a number of factors pointed to the use of interpolated inputs, and at minimum a comparison of techniques. The computational scaling involved in alternative future scenarios is illustrated in Figure 6-12 to Figure

6-15. Firstly, the longer-term aim of the entomological system under development is as a tool within a dynamic, integrated modelling environment. Predator, prey and crop models alike require the input of temperature amongst other variables (Figure 6-12). While such integrated model approaches will require additional computing overhead to provide estimates from two models rather than one, the opportunity exists to achieve relative economies of scale since interpolated temperature values need to be computed only once to drive two models. The modelling of either populations or phenologies for the purpose of managing outbreaks of endemic pests will involve multiple sequential surfaces, whichever interpolation technique is chosen. To produce daily output grids in the outbreak case, increases in computational intensity as a result of interpolating model inputs rather than outputs will occur as a result of added model runs over the complete grid. Additionally, computation time will be doubled through the need to compute two temperature surfaces (max and min) rather than a single interpolation of phenology data each day (Figure 6-13). The greater overhead of interpolating the inputs to the modelling may be justified in outbreak management, when the logical errors that arise when interpolating phenologies may not be acceptable.

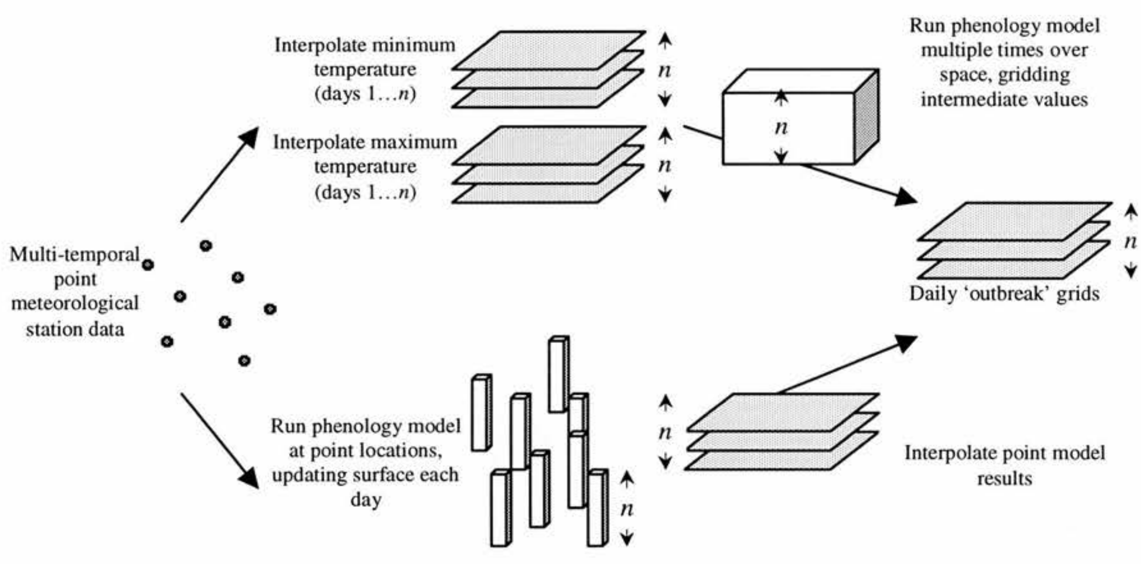


Figure 6-13. Outbreak scenario

Additional networks, that may supply further input variables in the future such as rainfall or relative humidity, are not necessarily likely to be sited together at the same given locations as the meteorological data stations used in this study. However, running a phenology model requires that all input data be available together at the set location. For the phenology-based interpolation method therefore, this would serve to constrain modelling to points where all inputs are collected. The number of point phenologies available for subsequent interpolation would therefore be much diminished, and much of the potential richness in input data would be unused. For distributed agricultural decision support systems of the future that might for example use a central server for the management of meteorological data and interpolation and client based pest modelling software, as with potential insect dispersal studies in which the spatial location of input data varies, interpolated inputs provide the only option (Figure 6-14, Figure 6-15).

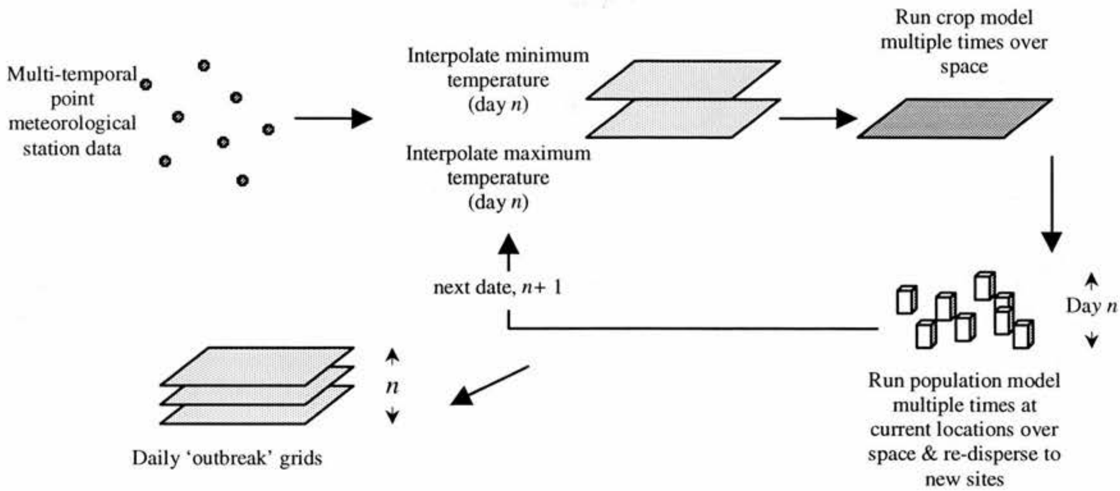


Figure 6-14. Modelling dispersal

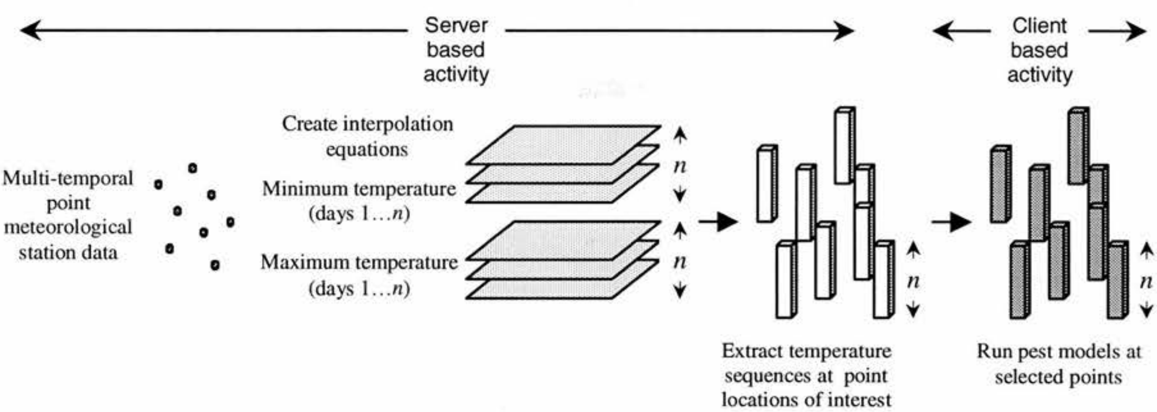


Figure 6-15. Distributed 'client based' DSS applications

As a more intellectual issue, when interpolating model results, the basis for selecting suitable variables to guide this interpolation process is much weaker (Grayson *et al.*, 1993), especially where the model is non-linear or contains multiple thresholds. Régnière (1996) however suggests that better ecological understanding is achieved by interpolating phenologies rather than temperatures. Given the empirical nature of the interpolation endeavour, the role of interpolation in this process seems far-fetched.

A final argument in favour of the more intensive strategy of interpolating input variables and then evaluating a pest model at multiple locations over a grid is that validating model output surfaces in the case of non-indigenous pests such as the Colorado beetle is impractical whereas both input grids and the biological model can be independently tested.

Table 6-6. Interpolate phenologies or temperatures? Advantages and disadvantages

	ADVANTAGES	DISADVANTAGES
Interpolate phenologies	• Computationally efficient; • Where a phenological model is based solely on the accumulation of temperature from one base, approximate linearities between development and height may be inferred and elevation used as guiding variable.	• Potential for 'over-smoothing' with most common interpolation techniques; • For models with multiple input types (e.g. rainfall and temperatures), difficult to justify selection of guiding variables; • Models with non-linearities and thresholds in temperature make simple relationships with potential guiding variables difficult to justify; • Results for different stages may be sequentially incoherent; • Difficulties in predicting zero development.
Interpolate temperatures	• Temperature surface smooth relative to expected phenological surface, so easier to interpolate and results visually acceptable; • Selection of gridded variables to 'guide' interpolation procedures justifiable on grounds of known physical processes; • Temperature surfaces may be used to assist phenological understanding e.g. exploration of super-cooling effects; • Temperature surfaces may be more easily validated than phenological ones; • Daily surfaces will be needed in future work, for example to link other interconnected variables such as crop yield or to model dispersion throughout phases of insect development.	• Time consuming to compute; • Standard GIS packages are unable to handle these volumes of spatio-temporal data; • Accumulation of error in temperatures may outweigh modelling non-linearity advantages.

These advantages and disadvantages are summarised within Table 6-6 for this particular case study. The practical problems of spatio-temporal modelling within present proprietary GIS favour the interpolation of model outputs (e.g. Johnston *et al.*, 1996). It may for example prove difficult to link the software with the high level code of the point process models, or to handle temporal sequences of interpolated data as anything but complete landscape grids. Obtaining simple 'drop point' cross validations as used throughout this study is likewise problematical. Furthermore, the interpreted nature of macro languages that add flexibility to proprietary software means that they are computationally inefficient in relation to directly complied code. The range of interpolation methods available within proprietary GIS software may not meet the needs of the sophisticated environmental modeller, whether one is intending to interpolate either model inputs or outputs. In this case it may be that interpolation will be by public domain or in-house code, as here. Then the barriers to interpolating model inputs rather than outputs relate more to computing power than structural constraints. Our experiments indicate an approximate thirty-fold increase in computing time when interpolating input grids and then modelling than by interpolating model outputs. These issues are summarised within Table 6-7 as a question set that could be applied in other ecological contexts.

Table 6-7.

	Interpolate inputs	*Interpolate outputs*
Limited computing power (PC environment)?		✓✓
Single output grid required?		✓✓
Smooth model results expected?		✓✓
Obvious gridded variables to guide model results?		✓✓
Single input type?		✓
Input variables perceived to be spatially 'smooth' relative to model outputs?		✓✓
Input variables known to be difficult to interpolate accurately?		✓✓
Model results easy to validate?		✓✓
Implementation entirely within a GIS?		✓✓
Multiple input types with sample networks of different densities?	✓✓	
Desire for further integrated modelling using similar inputs in future?	✓✓	
Multiple sequential outputs?	✓✓	
Model outputs difficult to verify?	✓✓	
Interpolated inputs of value in their own right?	✓✓	
Zero values in some output surfaces anticipated?	✓	
Lack of physical justification for guiding variables of model results?	✓	
Multiple input variables process guided by different variables?	✓	
Complex linked model with abrupt thresholds?	✓	

✓✓ - Recommended
✓ - Likely indication of 'best' practice

6.7 Chapter summary

- Within an entomological setting, analysing the propagation of spatial and temporal errors in model predictions charts a new research area. Previous studies have interpolated results from phenological models unquestioningly, without incorporating checks on the spatial and temporal integrity of the process;
- This chapter demonstrates the value of three metrics designed for the purpose of validating the performance of the particular interpolation approach adopted:
  - Comparison of root mean square accuracies between interpolation methodologies at known points;
  - Checks for logical consistency between temporal outputs;
  - Analysis of relative semi-variance in results between models run using actual input data, interpolated input series and interpolated outputs.
- The example of modelling the development of the Colorado beetle based on daily synoptic weather conditions shows that the common practice of interpolating the results of an at-a-point model will not *necessarily* produce results that are spatially and temporally coherent, even if point-based accuracy statistics (such as r.m.s.) seem satisfactory;
- Logical inconsistencies in biological sequence may arise when interpolating phenologies that are avoided when interpolating inputs prior to running the phenological models;
- Problems associated with the interpolation of calendar dates also arise only when interpolating model outputs;
- The interpolation of model inputs is also particularly beneficial for modelling the later stages of

insect development, where spatial association between phenological results may be highly localised in comparison to that of the daily temperature input data;

- Practical investigation of the question 'should we be interpolating inputs or outputs?' in relation to insect phenologies has resulted in a generic set of considerations that could be asked as part of the modelling process relating to issues of computing environment, model complexity and further use of the results;
- More generally, the work highlights the need for further research to combine spatial and temporal error propagation methods and the need to understand the spatial significance of attribute error.

7 Entomological applications

7.0 Introduction

This chapter focuses on practical applications of the system developed, in order to illustrate that the scientific understanding gained does indeed meet the requirements for producing nationwide estimates of phenology. By comparing the range of results obtained within the thesis with some examples of current practice to date, the assertion that geography matters in PRA and IPM is assessed to the degree feasible given the limited phenological focus of the work.

This chapter explores the use of geographical phenologies in pest risk assessment strategies (non-indigenous pests) and integrated pest management strategies (indigenous pests), the two application areas introduced within chapter 1. This chapter draws upon details of the particular phenology models for these insect pests linked within the interpolation system that were provided within chapter 3 (Section 3.1, p71), and the example outputs exemplified within chapter 5 (Section 5.1, p168).

7.1 Risk assessment for non-indigenous pests: probabilities of establishment

7.1.1 Introduction

The term 'pest risk assessment' (PRA) was introduced within Chapter 1 as the analysis of the risks posed by non-indigenous pests to the local plant health system (Phillips *et al.*, 1994). As Waage (1996) noted, '*Increased movement of alien pests due to changing patterns of trade, as well as their emerging importance as threats to biodiversity ... will require improved understanding of the risks posed by alien pests and introduced agents, as well as better mechanisms to inform and involve governments and scientists in self-regulation and sharing of benefits*'. Within the literature review of Chapter 2, the role to date of GIS and biological models in assisting with the assessment of the likely impact of a non-indigenous pest arriving in a country was discussed. Assessing the likelihood of a pest establishing itself, to which the techniques within this section contribute, forms just one element of pest risk assessment, itself a sub-component of pest risk analysis.

A number of research issues relating to assessing the likelihood of a pest establishing itself were identified within chapters 1 and 2, summarised as follows:

- The potential for a pest to establish itself is usually assessed using climate based information, of which temperature is most important for insect pests;
- This climate approach is more associative of insect phenology rather than population studies since estimating population also requires the consideration of natural enemies, the availability of food etc.;
- An 'Ecoclimatic index' is standard output from insect risk assessment systems such as CLIMEX. This is a relative measure that, while providing a useful summary, cannot be used to link the

timing of pest development with other elements of agricultural ecology (e.g. crop cycles);

- The potential ability for a pest to thrive is commonly estimated at only a limited set of point locations. To date, the merits of incorporating fully continuous geographical rather than phenologies based at a limited number of points as evidence contributing to the pest risk assessment process have been reviewed qualitatively rather than quantitatively (e.g. Baker *et al.* 1996).
- Previous geographical risk assessments have used landscape wide results, and where areas at risk have been associated with target crops this has been on a qualitative 'visual' basis only;
- Risk assessments have largely been made using long-term climate averages. Firstly, pest life stages are often shorter than the seasonal or monthly averages used. Additionally, this may have the potential to mask inter-year fluctuations and therefore dampen the likelihood of assessing extreme risks;
- Considerable scope exists for the coupling of phenology models with daily temperature data so that model results may more closely match the temporal scale of pest development and also exploration of the temporal variability in the limits imposed upon potential establishment by temperature;
- A revised spatio-temporal picture of the risks posed by insect pests may have the potential to improve our understanding of the behaviour of a pest under British conditions and to bring practical tools in support of political negotiations.

Colorado beetle is used as an example non-indigenous organism for the purpose of exploring these issues, the characteristic lifecycle of which was outlined within Section 2.1.1 (p30). This crop pest currently holds quarantine status in Britain as a result of pest risk assessments that recognise the beetle as posing an ongoing and considerable threat to British agriculture (Bartlett 1980). This status means that Colorado beetle is a common example chosen to illustrate risk assessment using point based techniques such as the CLIMEX modelling method (e.g. Sutherst *et al.* 1995, Worner 1988). The availability of such mapped distributions of potential establishment enhances opportunities for comparison. The focus on a single pest allows the implications of the spatial approach to risk assessment to be considered more fully. While the particular findings are pest-specific, the principles explored can be shown to have relevance to a broader range of risk assessment tasks.

7.1.2 Methodology

As a first step towards demonstrating the benefits of a geographical approach towards estimating the 'establishment' component of pest risk assessment, one may ask the simple question, 'Does a pest's phenology (developmental cycle) suggest that it might be able to establish in England and Wales?' By following this approach, it will be shown that it is feasible to make a preliminary estimate of the probability of establishment of a non-indigenous invader at locations throughout England and Wales. Employing measures of phenology alone for predicting establishment reflects a worst case scenario since it assumes that no factors other than temperature and photoperiod during development, such as lack of food, predation or parasitism, will limit the pest's survival. In this sense, the work has many links with previous climate based studies such as those using *CLIMEX*. Assuming that realistic models of a species phenology in relation to key abiotic factors are available it is suggested that, using the method developed in this thesis, it should be possible to determine the possible geographical extent over which a pest might establish. Information that might be produced to support the assessment includes an estimate of the maximum possible number of generations of a pest within a year and an answer to the most critical question regarding the possibility that a pest might develop to a stage that could allow it to survive over winter. If it cannot, any economic damage resulting from an invasion will be contained within one season unless the pathway to Britain reoccurs the next year.

There are a few examples where pest phenology has previously been modelled over space, mostly within the context of the North American forestry industry (Table 2-3). However, the contribution of those earlier studies was for short-term (within season) integrated pest management (IPM). Pest risk analysis (PRA) in contrast is usually assessed using 30-year climate records to assess long-term probabilities of establishment, as discussed within chapter 2, and this study is no exception. However, in contrast to previous work that bases assessments upon aggregated 'climate normal' data (e.g. Hulme *et al.* 1995), this chapter reports the variation in risk on a year-to-year basis *within* the 30-year period (1961-90). Additionally, in this study risk is assessed *throughout* the landscape, rather than solely on the basis of a limited amount of point data from meteorological recording stations.

7.1.2.1 Modelling framework

The geographical modelling framework outlined within Chapter 3 was used to drive the model of Colorado beetle phenology (Section 3.1.2). The model was driven using interpolated maximum and minimum daily temperature data for England and Wales, computed using partial thin plate splines to a spatial resolution of 1km^2 (Chapter 4). The general range of outputs resulting from the geographical framework linking the PETE model with parameters for Colorado beetle (Section 3.1.2) with spatial temperature data at a daily time step was introduced in Chapter 5. In this section, both gridded phenologies and cross-validated errors were targeted specifically to investigate the inter-year spatial variability of a pest's potential establishment.

Model runs were initialised at the beginning of the calendar year, and assumed for the sake of experimentation that a viable (nominal) population of over-wintered adults is present over each 1km^2 grid square represented. Phenological results for this case study focused on PRA are reported as the date in the year on which a cumulative proportion of this population (percentage emergence) reach the young adult stage, throughout England and Wales. In this section, runs of the geographical phenology system focus specifically on identifying areas where over 50% of progeny of the initial nominal pest population of overwintered, emerging adults would be able to survive to young adulthood by the end of the calendar year. Reaching this target event implies the possibility that these individuals could *potentially* make safe transit into diapause, assuming other limiting conditions such as available food were met. Alternative thresholds could be set by expert biologists for other specific tasks. For example, a target threshold of 1% young adults (or a less conservative 5%, given that model results will contain error) could be used to identify whether the potential for a pest to enter diapause, again assessed on the basis of temperature and photoperiod only. Given that the Colorado beetle is already known to have the potential to establish throughout much of England and Wales, low thresholds were not used in this example. The overall cumulative percentage of the nominal population leaving a particular stage can also be considered to reflect the probability of an insect reaching the following developmental state. Since only adult beetles are known to survive such winter conditions as found in Britain, mortality is implied where the adult stage has not been reached by the end of the model run.

Critical to long term pest risk assessment are the questions whether a pest has the potential to survive from generation to generation, and year to year. Model runs were therefore made for each year of the period 1961-90 throughout England and Wales in order to investigate the variability in the timing of insect development over this thirty-year period. This time span, which encompasses a broad range of temperature variation, is standard within risk assessments based upon climate data. The ability to translate this richness of geographical data into useful summary information of value to decision-makers is however critical.

Comparing results for years with extreme summer temperatures (e.g. 1976 and 1986) is one means of exploring the broad geographical boundaries of likely pest distributions. Detailed comparisons of Colorado beetle development were therefore made for the years 1976 and 1986, selected on the basis of the original temperature data to represent hot and cold summer temperature extremes respectively. These model runs were made using the same temperature input data from 174 meteorological sites throughout England and Wales as used in Chapters 4 and 5 (Figure 5-16).

A second means of summarising the variability in pest development rates that has a geographical context is the use of a binary threshold indicating for each grid location in the country whether a specific development point is reached within any one year. Using the nationwide grids indicating the Julian date of emergence for 50% young adults for each year between 1961-90 as a base, the maps were re-classified using a binary scheme according to whether this development stage was reached (1) or not (0). These 30 individual binary grids were then summed over the full 30-year period to provide an aggregate summary of geographical variation (0-30) in pest development, where 30 implies maximum risk. The result of this process is termed here an 'aggregate risk index'. Additionally, the annual Julian date values were averaged for each grid square over the thirty-year period. Since the dates at which the Colorado beetle might complete major phases of its lifecycle are important in tying development rates with crop cycles, these average dates of emergence have been computed only over the number of years for which the target event actually occurs. As reported in previous chapters, the calendar nature of the data otherwise strongly distorts the mean through the arbitrary dates (e.g. day 0 or 366?) for locations where an event in the lifecycle is not reached.

A geographical analysis of years with extreme temperatures or an exploration of establishment patterns on an aggregate index has not been feasible until now, since previous geographical work has been limited to using climate normal data that has been aggregated *apriori*. To accompany these geographical results, jack-knife cross-validation error distributions for 50% young adult emergence were also computed for each of the 30 years. In the case of non-indigenous pest risk assessment, the *under* prediction of risk is likely to have far greater consequence to Britain than over-prediction, within realistic bounds of scientific study. On the basis of the estimates of insect development computed using cross-validation versus actual model results therefore, errors of omission and commission were also computed (Table 7-1) for 50% young adult emergence of the Colorado beetle.

Table 7-1. Categories of error applied to r.m.s. verifications

		Results using 'actual' input data	
		Stage reached	Stage not reached
Results using 'modelled' data	Stage reached		commission
	Stage not reached	omission	

7.1.2.2 Experiments

Assessing areal risk statistics using gridded versus point-based phenologies

The geographical modelling system was used to estimate the date on which it might be expected that 50% of the Colorado beetles emerge from their pupae to become young adults, throughout mainland England and Wales, for each year between 1961-90. These results ('fully spatial' phenologies) were imported into a proprietary GIS and compared with spatially referenced point phenology results obtained by running the identical Colorado beetle model only at the locations of meteorological stations ('point' phenologies).

Summary grids were computed as outlined in section 7.1.2.1 to provide a spatial representation of

- The average Julian date at which 50% of the adults emerge from their pupae (reach 'young adulthood');
- The 30-year aggregate risk index (0-30) at all cells for this development target.

Using both point based and fully spatial results, the area of the landscape at risk per year (1961-90) was estimated. In the case of the point-based results, the area at risk was computed as a proportion of the overall area of England and Wales in accordance with the ratio of individual point phenology results that suggested development could occur to those where it did not.

Assessing the quantitative effect of incorporating crop data

International guidelines for pest risk assessment clearly suggest that assessment of a pest should be placed in the context of its potential economic, environmental and social impacts (Table 2-2). While the rate at which crops might be consumed is dependent on pest population dynamics, not phenologies, the spatial phenologies of this study serve to identify locations at which pests reaching damage-causing phases of their lifecycle might arise. Matching such locations with those where food is known to be available forms an initial step forward in the absence of models predicting population dynamics which, even for indigenous pests, are rarely combined with real geographies owing to their complexity as Leibhold (1993) notes.

Potatoes provide the main potential target crop of Colorado beetle in the context of England and Wales. Owing to the wide coverage of this crop and its economic significance, gridded digital data based upon MAFF parish-based census data are available that identify the number of hectares of potatoes per $4km^2$ grid square over the country for 1994. These were imported within the geographical modelling framework to provide a mask for the Julian date and binary grids and therefore to allow the measurement of the revised crop hectareage at risk. Statistics were generated on the basis of fully spatial and point results to assess the area of the landscape at risk under the target crop per year (1961-90). Analyses were generated on the basis of the presence or absence of the crop. The geographical software developed allows interpolation and model computation to be restricted to locations where crops are present on the basis of this digital data.

7.1.3 Results

7.1.3.1 Continuously gridded versus point based estimates of areas at risk

Estimates of risk

Maps reflecting the temperature limitations on the potential development of Colorado beetle in England and Wales over the 'climatic normal' period (1961-90) are illustrated within Figure 7-1. These show the potential of a pest to develop through a single generation, from an over-wintered immature adult to the next generation of young adults (50% emergence). The distributions presented reflect the marginal location of England and Wales for this pest, with the most northerly and upland areas not expected to be threatened under current climate conditions. In upland areas a small minority of pests may only receive sufficient day degrees for development to reach young adulthood as late as the end of December (Julian day 362). The majority of development to young adulthood, where it occurs, is finished by the end of October.

Further south, the average expected date of emergence for the pest to reach the adult stage is earliest in areas of lowest topography and hence warmest conditions (Figure 7-1(a)). The earliest dates are encountered towards the end of August (Julian day 246). Consideration of these dates is significant since in order for the adults to enter diapause (winter resting), they require to be well fed. The potato crop in Britain is generally harvested between mid September to mid-October (Jellings and Fuller

1995), and beetles feed on the haulm which is usually destroyed shortly before the potatoes themselves are lifted. Analyses of Figure 7-1(a) suggest that in the majority of agricultural areas, emergence might occur before the end of October. The figures therefore indicate that there may be significant areas of southern England where *both* emergence might occur and satisfactory diapause may be feasible because adequate crops are still in the ground.

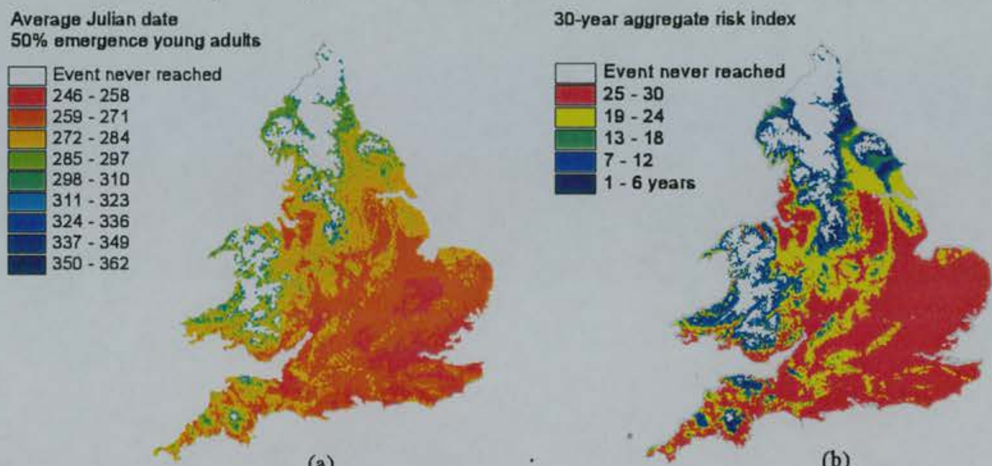


Figure 7-1. (a) Average Julian date at which 50% emergence of young adults might occur and (b) the probability of this event occurring on the basis of long term daily temperature records

While Figure 7-1(a) may be used to associate potential emergence dates with the crop cycle, it provides an average picture rather than reflecting the inter-year variability of an event, in this case 50% adult emergence, occurring. Figure 7-1(b) in contrast represents the consistency with which 50% adult emergence might occur over England and Wales. The cumulative aggregate risk index incorporates a probabilistic element to the overall results by allowing an assessment of the likelihood of risk (e.g. 20/30 years). The likelihood of a pest establishing is greater where conditions favour the re-emergence and build up of a population from year to year, for example within the agricultural areas of southern Britain (values 25-30, coloured red within Figure 7-1(b)). Measures such as the long term average number of generations by latitude computed using CLIMEX (e.g. Sutherst *et al.* 1995) mask such inter-year variability which has the potential to contribute strongly to the long term establishment of a particular pest in addition to assessments of economic damage.

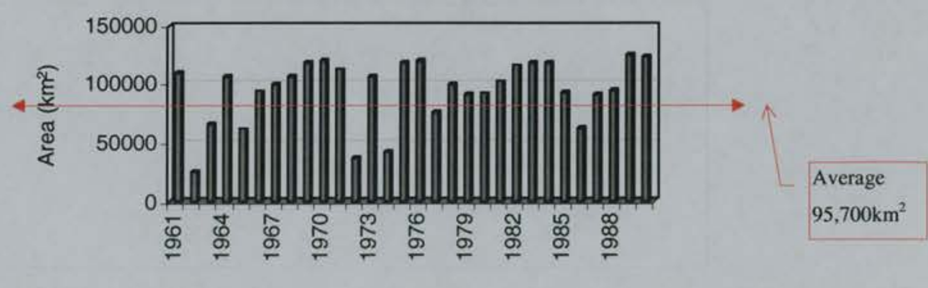


Figure 7-2. Inter-year variability of total land area of England and Wales potentially at risk from Colorado beetle, *Leptinotarsa decemlineata* (1961-90)

This geographical portrait of inter-year variability in pest development is complemented by Figure 7-2, which plots the overall variation in the area at risk from year to year within the 30-year climate period. As the plot demonstrates, few years conform to the 'average' and significant variation about the mean can be identified. The figure shows a degree of negative skew, with 1962, 1972, 1974 and 1986 strongly unfavourable for development, whereas 1970, 1976, 1989 and 1990 are years in which the average is most exceeded. While on average the area over which development to young adulthood is possible is 95,700km^2, the standard deviation of area at risk is high at 26,800.

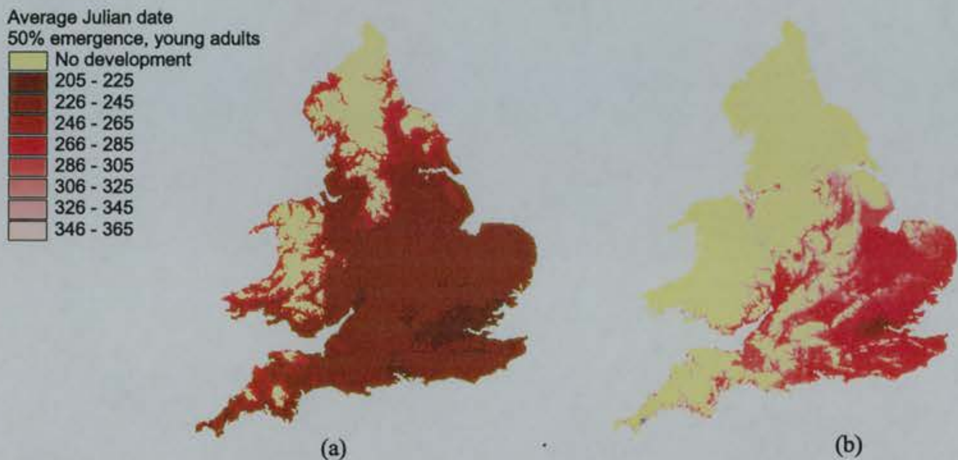


Figure 7-3. Average Julian date for 50% emergence of young adults from their pupae (a) 1976 and (b) 1986

Figure 7-3 maps the distribution of expected dates of emergence for young adult Colorado beetles (50% emergence) for the years 1976 and 1986. Earliest emergence generally occurred in the south and south east of the country in both years, but in 1976 was on average one month earlier than in 1986. Emergence also occurred throughout the south-western counties (with the exception of upland moorland areas) in 1976, but was confined to the most sheltered coastal locations of Devon and Cornwall in 1986. This pattern is generally what would be expected, resulting largely from the transition to more favourable to less favourable conditions for development along the broad south to north climate gradient but also conditioned by topography. The figure demonstrates the use of the geographical phenology system designed for the thesis to assist in the construction of 'best' and 'worst case' scenarios. Note for example that the earliest data of emergence for Colorado beetle young adults (50% emergence) on average over England and Wales is Julian day 246 (Figure 7-1(a)), while in 1976 emergence starts from date 205 (Figure 7-3(a)): a full month earlier. Previous work based on averaged 'climate normal' temperature data has lacked the flexibility to provide the opportunity for such scenario building since the input data is averaged prior to analysis. These results suggest that these is potential for extreme risk to be underestimated in PRAs that use climate normal data, especially where cropping cycles are short.

It is interesting to observe that, while 1976 and 1986 were viewed as extreme years on the basis of analyses of the original point temperature data used for the thesis, these do not necessarily represent years of extreme risk to Colorado beetle as computed using the geographical phenologies (Figure 7-2). This discrepancy may arise in part as a result of the complex nature of the Colorado beetle model used, which incorporates not only accumulations of temperature over multiple base temperatures and thresholds but also reflects photoperiod. It may also indicate that point data at meteorological stations may not provide an adequate reflection of pest activity at locations that are marginal for development, an issue explored further below.

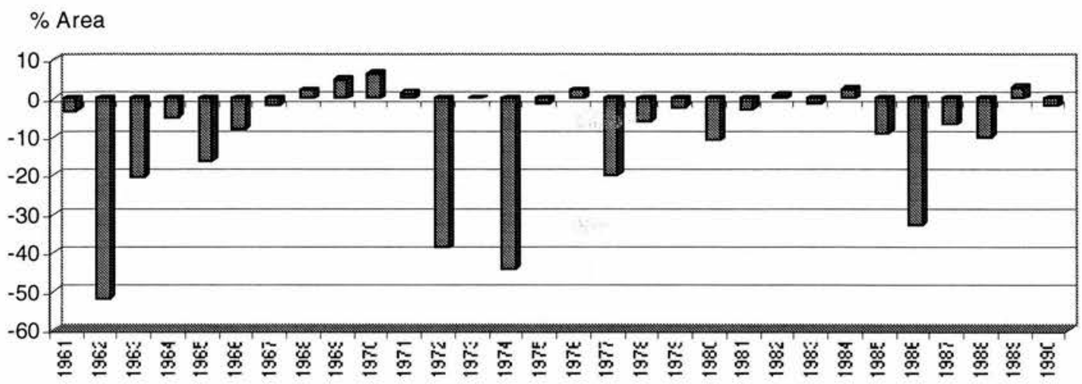


Figure 7-4. Total area of England and Wales at risk (likelihood of 50% emergence adult Colorado beetle) computed using geographical phenologies minus area assessed to be at risk on the basis of model runs solely at meteorological sites

Inference regarding the establishment of a pest is most commonly carried out using point based data at locations where meteorological data are available (e.g. Sutherst *et al.* 1995, Worner 1988). Fluctuations in the difference between point and interpolated results for the Colorado beetle 50% adult emergence scenario are illustrated within Figure 7-4. This compares the percentage of the landscape considered at risk between the point-based averages and the 'fully spatial' model results on an annual basis. While in 1976, the point-based results estimate a slightly lesser area of England and Wales at risk in comparison to the fully spatial data, in 1986 and in several other years they estimate a much larger area to be at risk than the fully spatial approach. In numerical terms, the point phenology results strongly over-predict the area at risk relative to those computed using gridded data (Component years of Figure 7-1), with an average relative over-prediction of 14%. In the minority of years where this situation is reversed, it is by a small margin in comparison (2.5%). Discrepancies are particularly high for 1962, 1974 and 1986. These were all relatively cool years. This does suggest that, since the meteorological sites have a tendency to be preferentially located in lowland areas, in years where development is curtailed abruptly in higher areas (colder years) owing to the use of hard thresholds within the model (Appendix 6) this may not be well reflected in the point-based figures. Where development still occurs (but less rapidly than at lowland sites) in upland areas (hotter years) the discrepancy between figures will be less marked.

Error analyses

The annual variability in the area assessed to be at risk of Colorado beetle establishing in England and Wales, presented in the previous section as an aggregate risk index based upon 30 years of data, introduces an element of uncertainty which can be used to accompany the average risk statistics. This is important since *average* risk is not as great as the *extreme* risk, as demonstrated in Figure 7-2 and by comparison between Figure 7-1(a) and Figure 7-3(a). The earliest date on which a pest may reach 50% emergence of the young adult stage within Figure 7-3(a) for example is a month earlier than the first date when looking at the map of the average distribution (Figure 7-1(a)). This suggests that assessments computed on the basis of climate normal data may underestimate the risk of a pest establishing in the country.

Validating the performance of the geographical modelling approach is equally important. Following the procedure described in section 7.1.2.1, estimates of pest development computed using jack-knife cross-validation were compared with those computed using actual data to provide a measure of the degree to which the geographical approach has a tendency to under or over-estimate risk (errors of omission/commission respectively, Table 7-1). The value of this approach is to focus the consideration of uncertainty onto the decisions which rely on it (i.e. risk/no risk?), rather than the underlying information (i.e. Julian dates, as previously).

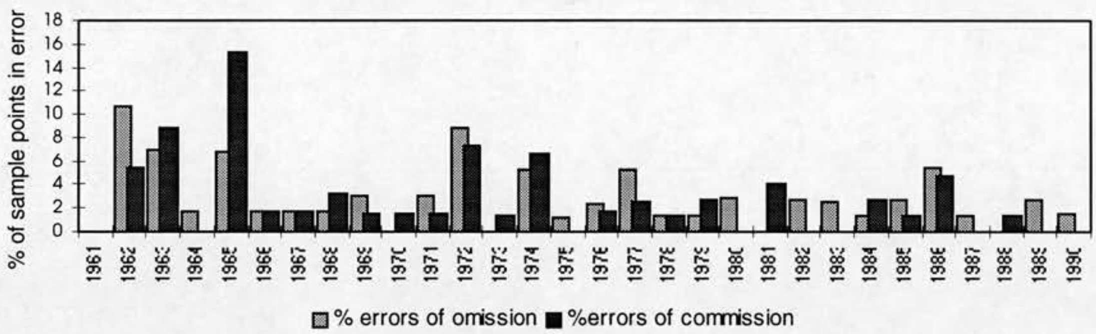


Figure 7-5. Degree of under or over prediction of risk assessed according to whether a pest reaches young adulthood (50% emergence) before the end of a calendar year within the geographical phenologies, 1961-90

Figure 7-5 illustrates the overall degree of under or over-estimation inherent in the use of geographical phenologies for assessing pest risk in comparison with the use of point-based data. The errors or omission/commissions are presented as the proportion of the original temperature data locations at which such problems arise. The results again suggest that the greatest difficulties arise when modelling phenologies for cooler years (1962, 1965, 1972, 1975, 1986), but that neither under or over-prediction dominates.

7.1.3.2 Crop limited risk assessments

Relevant digital crop data were incorporated as a mask over the previous results (7.1.3.1) to eliminate areas not under the relevant potential host potato crop. The revised plots are illustrated within Figure 7-6. Figure 7-6 (a-b) reveal that only to the extreme north of the country are potatoes grown in areas that may, on temperature grounds, be unsuited for the establishment of Colorado beetle (coloured black). Moving beyond the visual display of data, this section establishes what the effect of incorporating this potato data on the overall risk statistics amounts to.

Figure 7-7(a) demonstrates that basing areas at risk on gridded phenology results without modification for areas under the relevant crop results in a gross over-estimation of the potential area of the most serious category of potential Colorado beetle. This amounts to 19% of the overall area of the country, higher than the overall area in which potatoes are grown. Without modifying risk assessments according to the availability of food therefore, there is a danger that risk to commercial crops may be grossly overestimated. However, Colorado beetle may be able to exist on weeds such as *Solanum dulcamen* or in private gardens, so extending the area at risk. An assessment of the area at risk based on the proportion of the point data at risk multiplied by the overall land surface, and the crop-masked geographical results in proportion to the overall cropping area, show strong agreement (Figure 7-7(b). This suggests that, even without the geographical phenologies, the estimate of commercial damage to potatoes may be adequate. Comparison between Figure 7-7(a) and (b) does suggest that for a crop growing in predominantly upland areas, for example areas of forestry susceptible to gypsy moth, this outcome might be different.

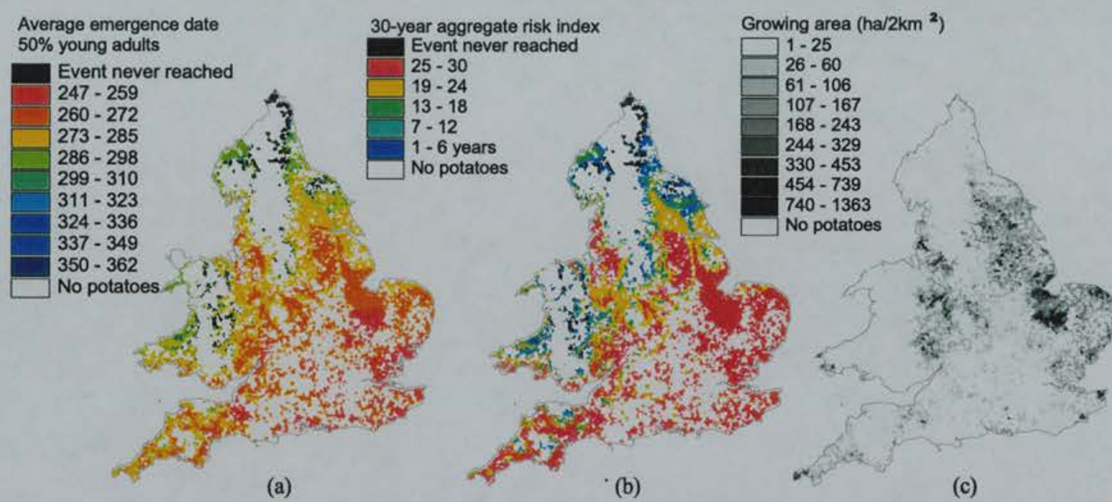


Figure 7-6. (a) Average date at which 50% emergence of young adults is reached, and (b) Cumulative survival potential index, with Colorado beetle *(Leptinotarsa decemlineata)* in areas of potato cropping together with (c) Distribution of potato crop 1994

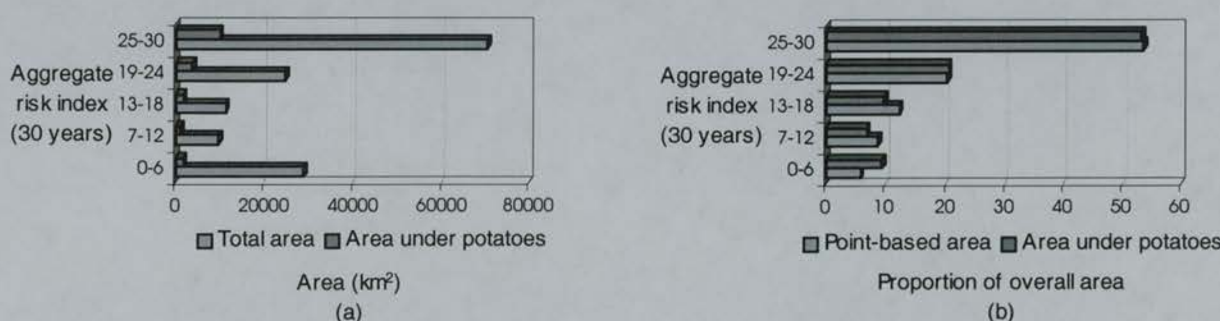


Figure 7-7. (a) Total land area estimated to be at risk on the basis of masked and unmasked geographical phenologies and (b) proportion of land area at risk on the basis of point based versus masked geographical phenologies

7.1.4 Discussion

7.1.4.1 Risk assessment framework

Before assessing the detailed results of section 7.1.3, it is useful to contextualise discussion of this work in relation to current standard practice. As has already been noted within chapter 2, climate data are used to assist with the assessment of the limits to pest establishment, and CLIMEX (Skarratt *et al.* 1995) is a tool commonly used to this end. Figure 7-8 below illustrates standard outputs from CLIMEX in relation to the Colorado beetle. These results are constructed using biological parameters derived from the literature (Sutherst and Maywald 1985).

As Figure 7-8 shows, these outputs are point based, and within the confines of England and Wales are based on data from 15 meteorological locations in total. Additionally, they were constructed using climate normal data from 1931-60. These figures represent the number of stations commonly used within practical risk assessment procedures, although there is no theoretical limit to the number of stations within the system and within a British context many more could be added as in this study. The incorporation of gridded climate normal data within CLIMEX has however more recently been undertaken in a pre-cursor to this study (Baker 1996), and negotiations are under way to make this part of the core functionality of that system. Reports assessing the effect of these spatial data on the aggregate area estimated to be at risk in comparison with the point-based approach have not however been found within the literature.

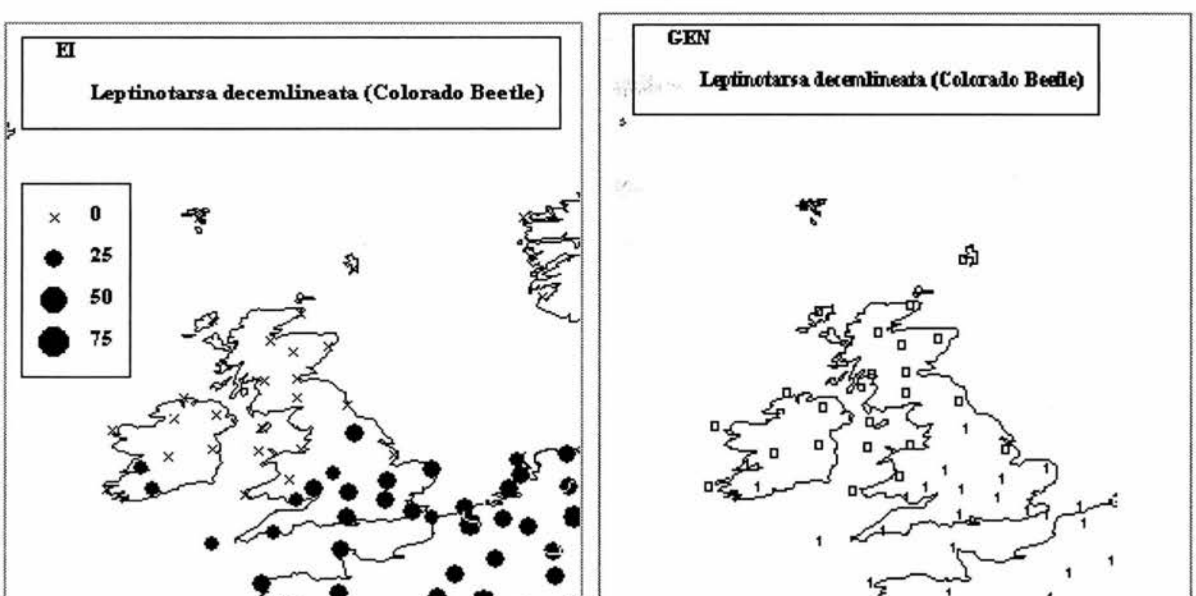


Figure 7-8. CLIMEX outputs, (a) Ecoclimatic index for Colorado beetle potential development and (b) Number of potential generations

In contrast to the results of Figure 7-1, the CLIMEX based figures (Figure 7-8) do not express year-on-year variability of risk but are rather based upon the long-term climate averages. The ecoclimatic index provides a relative measure of the beetle's ability to thrive, based on pre-specified climate limitations, but cannot assist in tying the timing of particular pest life stages with crop cycles owing to the absence of calendar-based information. The time of sowing and the subsequent timing of critical, susceptible growth stages in relation to coincidence with pest attack can greatly influence the influence of a pest (Oakley 1997). The quality of available food is known to affect survival probabilities significantly for Colorado beetle, for example (Bartlett and Murray 1986). At the very broad nationwide wide however, the general pattern in pest risk presented is similar. The ability of the pest to survive through a generation (Figure 7-8(b)) is similar to the use of the aggregate risk index in Figure 7-1(b), but without the added probabilistic element. As Figure 7-9 shows for *Bemisia tabaci*, the computation of numbers of feasible generations is equally feasible within the framework developed for this thesis although is not expressly incorporated within the results of this chapter.

7.1.4.2 Point versus gridded phenologies in support of pest risk assessment

The marked differences in survival percentages indicated within Figure 7-4 between aggregate data computed using fully spatial and point based methodologies indicate cause for concern over the representative nature of point statistics for pest risk assessment. Without interpolation, climate based studies are inherently dependent on the location of meteorological stations. The finding that using point data instead of fully gridded phenologies causes the overstatement of pest development potential in this case may be attributed to the overall tendency for the height distribution of meteorological stations to be biased towards lower levels in comparison to the landscape as a whole. The data set of 174 points throughout England and Wales used in this study is however typical in distribution and volume of the real-time UKMO synoptic network, which shifts from year to year with the relocation or closure of recording stations. As Figure 7-8 illustrates, the number is considerably higher than that commonly used in PRA.

Given that in assessing risk a degree of cautious overestimation may be circumspect, the overstatement of development potential presented by the point-based results is a discrepancy in the preferred direction. Nevertheless, overestimating the land area at risk in England and Wales by 30% of the land surface of England and Wales in a minority of years (1962, 1972, 1974 and 1986) suggest the possibility for overstatement in climate based arguments for quarantine cases based on limited, unrepresentative, point based results.

The dangers of using temporally averaged figures for risk assessment are highlighted within Figure 7-2(b) and Figure 7-4. These indicate there is a possibility of underestimating a pest risk problem in particularly warm years: in twelve of the thirty years, the area estimated at risk is greater than the average. These results suggest that extreme but potentially significant events maybe under-represented when assessing establishment probabilities for a pest using long term climate average data. This however is the means by which the majority of geographical and non-geographical assessments are made within the literature (e.g. Tiilikkala *et al.* 1995, Braasch *et al.* 1996). Practical experience in PRA with karnal bunt (Sandsford and Baker 1998), a crop disease potentially important in extreme years only, serves to highlight the potential dangers of 'climate normal' based techniques in isolation from considerations of inter-year variability. Others have questioned the representativeness of point based data for ecoclimatic studies, and have suggested that problems may arise when using long term averaged data through the understatement of inter-year/intra-year climate variance (Bennett *et al.* 1998). The results of this study, which explores these issues directly, confirm what has previously only been hypothesised.

7.1.4.3 Towards economic assessment: the incorporation of crop data

The phenological approach used in this study allowed the broad-brush comparison of insect development times with standard cropping cycles in England and Wales. However, dates of planting and harvest will vary according to location, year and variety. For many crops, the accumulated temperature model implemented within this study might serve to assist in matching pest development cycles to the agricultural cycle in a more detailed fashion. However, both the general development of potatoes and their harvest dates are significantly limited by moisture in addition to temperature. This study therefore focused on the effect of assessing pest risk according to recorded crop location, rather than the overall landscape or a hypothetical agricultural landscape.

In this particular case, incorporating areas of potato cropping had little effect on the overall figures for the area at risk from Colorado beetle in relation to those computed at the available meteorological sites alone. Potatoes grown other than for seed tend to be sown on lower ground, such that the configuration of meteorological sites is representative for this crop. The results suggest that shifting the areas under potato production to slightly higher ground or further north would not provide a feasible means of defence against Colorado beetle should it become established. The implication of the larger difference between point based figures and those for the wider landscape is that comparative estimates for a potential upland pest, for example a wood boring organism in forested areas, could be seriously overestimated using the point based methodology.

From a geographical scaling perspective, the use of digital data from one year alone (1994) represents a representative snapshot of the area at risk in any one year and therefore would be used mainly as an annual economic assessment. It is likely however that the commonly used four-year rotation for potatoes practised to minimise crop diseases in particular would cause only small relative shifts in Figure 7-7(b) because this is already based on a 2*2km aggregation of cropping data. Changes in agricultural practice, and in particular the effect of farming subsidies and markets on the worth of the potato crop, are likely to have a more significant effect on potato distribution from year to year. Previous work within the literature that has incorporated digital crop data has interpreted the results on a visual basis only (e.g. Braasch *et al.* 1996), rather than through a quantitative assessment of the area at risk as in this case.

As Waage (1996) points out, the threat posed by an invasive alien species goes beyond the agricultural arena to impact upon conservation issues. Indeed, it has been suggested that in some countries alien species pose the greatest risk to the conservation of biological diversity (Schei, 1996). While the focus in this study has been on the agricultural system, the broad geographical coverage across all environments that has been facilitated within this thesis means that different classes of land cover or habitat in more remote areas could equally be explored in future work.

7.1.4.4 Strategic issues

A number of broader issues relating to the underlying methodology used in the previous papers on the topic of mapping establishment probabilities, using for example the CLIMEX system, also deserve discussion. In particular, employing measures of phenology alone for mapping establishment implies the worst case scenario as does the starting assumption that diapausing (winter resting) adult pests are present throughout the landscape at the beginning of a year. It assumes that no other limiting factors which include competitors (e.g. Davis *et al.* 1998), lack of food at critical periods (e.g. Oakley 1997, Holland 1997) and natural enemies (e.g. Ohgushi and Sawada 1998), affect the pest's chances of survival. For pests with high fecundity and those adapted to intensively farmed monocultures (such as Colorado beetle), availability of a suitable source of food may be a particular threat to long term survival (e.g. Hough-Goldstein *et al.* 1993).

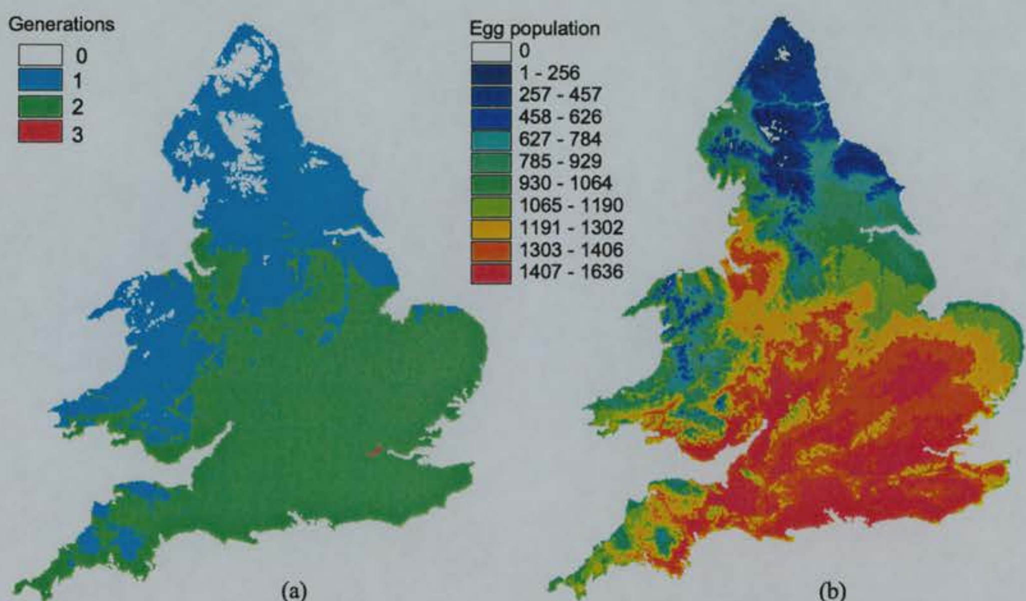


Figure 7-9. Tobacco whitefly (*Bemisia tabaci*) (a) Expected number of generations and (b) Potential eggs populations from an initial population of 10 adults, 50 eggs and 10 larvae 1976

The reliable applied population models needed to determine probable levels of crop damage and economic impact are commonly unavailable since, even for native species, the number of factors combining to influence population numbers, both directly and indirectly, are many (Leibhold, 1993). Examples of varying development rates between different populations (e.g. Peterson *et al.* 1998) or populations on different host crops (e.g. *Bemisia tabaci*) abound. These problems are exemplified within Figure 7-9, which maps potential outdoor populations and generations of *Bemisia Tabaci* in

Britain on the basis of a model run using daily temperatures alone. Despite the presence of the pest in greenhouse environments, this pest has not to date posed a particular problem to the horticultural industry as the figure would suggest, implying the important role of natural enemies and the scattered nature of relevant host crops in its distribution. In a pest risk analysis context, biological knowledge may be unable to sustain the technical possibilities presently afforded by integrated geographical modelling.

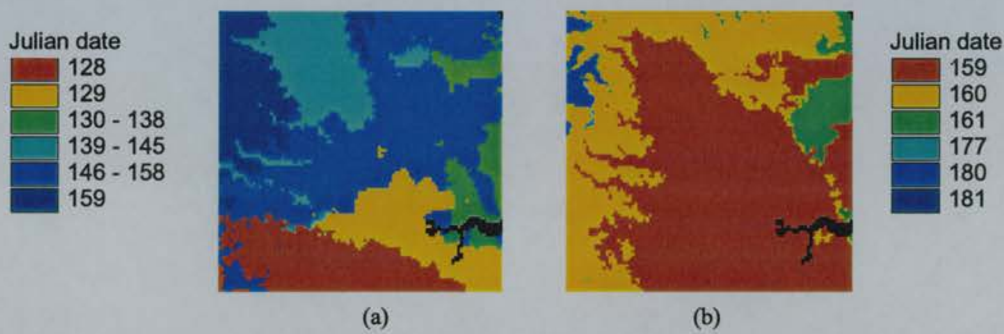


Figure 7-10. Date on which threshold temperatures of 25°C and 20°C were first reached, Vale of York, 1976

The relative simplicity of insect phenology, in contrast to insect population numbers, makes it more likely that models for the development for a variety of insect pests common within other trading countries (e.g. *Bemisi tabaci, Liryomyza huidobrensis, Thrips palmi*) exist or are under development. One country's endemic pest, for example Colorado beetle in the United States or Codling moth in Great Britain, may warrant assessment as an exotic species requiring quarantine in another (e.g. Britain and Japan, respectively). As explained within Chapter 3 (Figure 3-21), the flexibility of the geographical modelling system used allows other temperature-dependent models to be slotted into the analysis framework as extra modules. Examples could include accumulated temperature thresholds from a model bank (e.g. University of California Statewide Integrated Pest management Project Phenology Model Database, http://www.ipm.ucdavies.edu) or models incorporating more complex pest interactions. Exploring the likelihood or timing of flight according to minimum temperature thresholds associated with long distance pest movement (Figure 7-10) could also provide further information useful when assessing the threat of a pest establishing within the country.

When using phenological models for risk assessment, a number of uncertainties arise. The choice of a 50% 'cut-off' incorporated within the binary risk index to indicate the possibility of a pest completing a single generation is a matter for further biological debate. Others may prefer the use of more conservative aggregate risk indices at lower thresholds of adult emergence, such as 1% or 10%, to determine whether any potential for a pest to thrive from year-to-year exists. In the context of this study, the aggregation of these binary indices rather serves to illustrate the variability of the phenomenon being modelled. This could equally be used to investigate whether the crop cycle for potatoes ties in with the potential presence of larvae, for example.

The ability of a pest to over-winter in a particular environment is in itself a highly complex subject (Leather *et al.* 1993) and previous work has shown that it cannot be attributable simply to climatic thresholds. Bartlett and Murray (1986) for example point to mortality rates of up to 80% for Colorado beetles during diapause. The degree of feeding and reproductive ability prior to diapause, soil type, precipitation, and waterlogging are thought to be additional factors affecting survival in addition to temperature. This caveat applies both to CLIMEX and tailor-made phenology models, although a greater degree of flexibility exists within process-based models to incorporate such knowledge as it became available. CLIMEX however does attempt to incorporate winter minima and rainfall, albeit on a monthly, climate normal basis. The daily modelling scale used in this study for example would allow the consideration of daily fluctuations in temperature above and below a critical point that would inevitably be masked when using monthly data. The value of the geographically based average emergence dates and aggregate risk index in comparison with outputs from CLIMEX show greater flexibility and depth of information. They provide a gauge as to whether a pest is unable to survive the cropping period on the basis of ambient temperature, and thus the hazard it poses within any one year. As Figure 7-11 demonstrates the system provides scope for further temperature-related analyses in the future, for example in relation to overwintering thresholds or fluctuations.

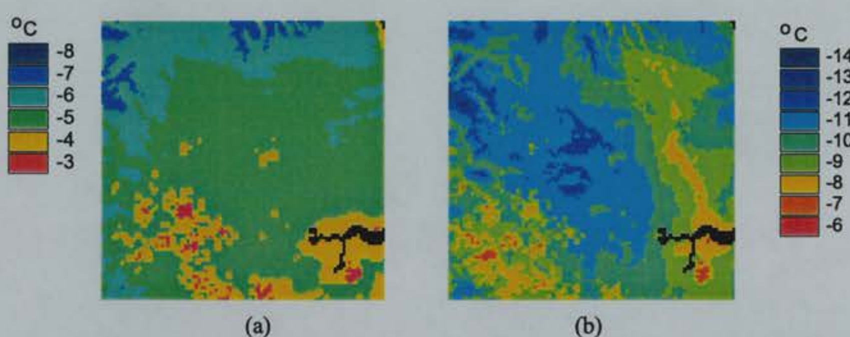


Figure 7-11. Estimated absolute minimum air temperatures (°C) for the Vale of York for (a) 1976 and (b) 1986

For exotic non-indigenous pests the likelihood of finding detailed phenological information without recourse to laboratory experiments is low (Baker and Bailey, 1979). In such cases, there is little alternative but to use inductive methodologies such as those of CLIMEX to support an urgent pest risk assessment. Where a phenological model, or indeed accumulated temperature information, is available, the value of the approach explored lies in its ability to account more closely for the underlying pest biology from a deductive science base and to identify the magnitude of inter-year variability in risk. Especially where the quarantine case for a relatively well known pest comes under review or is in dispute, the framework allows greater scope for multiple analyses and more fully integrated explorations contributing to the assessment of socio-economic risk. Computationally, the cost of calculating fully gridded phenologies over 30 years on the basis of interpolated daily temperatures is however high, although manageable using the workstations of today.

The caveats relating to the complexity of the overall biological system make it imperative that the spatial results are interpreted carefully by a biological expert and subjected to a number of further sensitivity analyses. Henderson-Sellers (1996) commented regarding potential scenarios of climate change that these should be seen as '*sketching images of the future*' and providing '*vague contours of the plausible* ...', and so should these geographical impressions of pest risk also. Different parameter settings and modelling structures might for example be investigated to scope the overall pest risk assessment problem and build a consensus of opinion. As King and Kramer (1996) note, '*Modelers should avoid believing or giving the impression that their models hold the 'answers' for policy makers. They hold, instead, the refined results of particular points of view.*' The unparalleled multiple options provided by the modelling framework developed for this thesis, from mapped average emergence dates at multiple stages, activity indices, risk indices to the variation in their annual statistics from year to year could be used as a supportive suite of information from multiple perspectives rather than the present reliance on a single style of mapped outputs. Consideration of uncertainty both in terms of probabilistic aggregate outputs and through the use of cross-validated error statistics provides additional evidence for the scientific validity of the geographical approach. It is the integrated nature of the geographical/biological modelling approach, rather than the simple visualisation of these component parts as has been previous practice in much of the PRA literature, that has achieved the improved range of results. In turn, this may lead to a broader understanding of the scientific conclusions and their sensitivities at a management level.

The risk measures presented within this section suggest that the major goal of the work from an applied biological perspective, to provide more objective and balanced science as demanded under international agreements in support of quarantine decisions, has been realised. Goodchild (1993, p14) suggests to GIS practitioners that '*We spend vast sums on collecting raw geographic information with technologies such as remote sensing, and on modelling environmental processes, and yet it often seems that the biggest problem of all is the translation of this knowledge into useful and effective policy.*' The methodologies presented show the value of geographical phenologies as one element of the wider scientific toolbox that form part of a pest risk assessment, itself a subject area inevitably driven by political decision makers.

7.1.5 Summary

- Data generated from the integrated geographical-entomological modelling system could be used to support the case for a pest's quarantine status within a pest risk assessment. This has been illustrated for England and Wales using Colorado beetle (*Leptinotarsa decemlineata*) as an example;
- The incorporation of explicit phenology models, rather than an ecoclimatic index as used previously, allowed the date-based results to be tied in with the cropping cycle;
- The integrated system was used to quantify differences between modelling pest phenologies at sites determined by the location of meteorological data versus insect phenologies computed using gridded sequential interpolated temperatures as inputs;
- An aggregate risk index was introduced as a probabilistic representation of the likelihood that

a pest might complete a single generation over the 'climate normal' period (1961-90) throughout the landscape on the basis of daily maximum and minimum temperatures.

- Investigations into the inter-year variability of establishment risk based on one parameterisation of the potential survival index show the standard deviation in area (26,800) to be high relative to the average proportion of the landscape potentially at risk (95,700km^2). This suggests that previous work using climate normal data may mask extreme, but potentially significant risk. The earlier work ignores the assessment of year-on-year consistency in pest development in given locations as one means of analysing the likelihood of long-term establishment;
- Results indicate the tendency for point based statistics to overestimate risk in relation to results from fully spatial assessments in the majority of years (21/30 years). The average overestimation of land deemed to be at risk over England and Wales was 14%. In the less frequent cases where relative underestimation arose, this affected only an average 2.5% of the overall landscape area. Underestimation was most marked in predominantly cold years (e.g. 1962, 1972, 1974, 1986);
- Assessments were modified to take account of the main host crop, potatoes, using gridded digital crop data ;
- The results, unlike the main body of work in pest risk assessment, reflect more fully the underlying variability and degrees of sensitivity of the pest or disease to differences in climate, owing to the use of daily input data;
- The broad suite of available results, both in terms of spatial coverage, output flexibility and error assessment, contrasts markedly with the restricted output from systems currently in use;
- Linking with the results from previous chapters, the methodology will also support spatial estimates of pest risk on the basis of empirically derived accumulated temperature envelopes or temperature-driven population models to provide a flexible suite of outputs for consideration as part of the overall pest risk assessment process;
- Temperature is not the only factor affecting pest survival, and other information regarding interactions between other pests and the crop environment are needed. The flexibility of the modelling environment relative to those of fixed structure such as CLIMEX nevertheless affords the opportunity to incorporate such knowledge as it becomes available, providing a bridge between .pragmatic and more complex research models;
- Modules that more adequately consider the ability of a pest to survive over winter in Britain would be a particularly useful addition to this geographical pest risk assessment suite;
- As the example for *Bemisia tabaci* showed, one important value of the system is to illustrate weak areas in the biological knowledge base. All outputs should be .carefully weighed by a biological expert, and viewed in conjunction with results from other approaches to PRA rather than in isolation.

7.2 *Indigenous pests: Codling moth (Cydia pomonella)*

7.2.1 Introduction

Within Chapter 1, the need for integrated pest management was introduced from both environmental and productivist perspectives. This holistic approach, in contrast to previous strategies relying solely on chemical products and using prophylactic spraying, factors multiple strategies such as chemical and biological pesticides and the introduction of natural enemies into pest management plans. Given the complexities of the agricultural environment, large growers cannot afford the risk of ignoring chemical strategies: rather, these are being more carefully targeted to minimise production and environmental risk. Phenology models form one means by which both biological and chemical control options are better targeted. However, where spatial entomological modelling is found within the research literature, it is rarely carried out in reference to geography, and is therefore of limited practical use. As highlighted within Chapter 2 (Section 2.2.2) most geographical work concerning pest management to date has been based on large volumes of empirical pest population data collected from traps (e.g. Liebhold *et al.* 1993). In a British context, the underlying intensive sampling programmes that would allow the adequate assessment of local spatial autocorrelation across England and Wales are relatively unknown.

Within agriculture and horticulture, as in many other areas, computerised decision making tools which incorporate models of insect phenology are becoming commonplace (e.g. DESSAC, MORPH). The models driving such systems continue to grow in sophistication and predictive ability and are moving towards improved integration between individual components of the system. The transfer of applied biological models from research laboratory to general use by the agricultural community has however met with mixed success. The reasons for this slow uptake are many, ranging from the complexity of the underlying biology which makes accurate models difficult to achieve to issues relating to the usability of the software packages themselves. The focus in such recent projects to date has therefore been largely on improving skills in interface decision and communication of advantages/risk.

The biological research effort associated with recent DSS initiatives focuses almost exclusively on improving the targeting of control measures through the development of a closer understanding of the *temporal* rather than *geographical* dimensions of pest biology. To some extent, consideration of input data required to drive this variety of models within decision support systems (DSS) has been left behind. Issues passed over include both the distribution of driving inputs (e.g. daily maximum and minimum temperatures) to users in addition to questioning how spatially representative data, either at points or from crude interpolations, are for the modelling purpose. Loucks (1995) writes in his general critique of decision support systems within a water resources context that '*The input and output data requirements are explicit in the DSS design documentation. All that remains in this task is to present the input data in a form that facilitates their [DSS] assembly*'. This downplaying of input data considerations is clearly an issue that transcends insect ecological applications. The focus of this section is therefore to investigate the potential contribution of continuous spatially referenced input data to agricultural decision support frameworks using phenology or population models, focusing specifically on daily maximum and minimum temperatures as in previous chapters.

As discussed within Chapter 2, the de-facto source of input data within an applied modelling context is the nearest meteorological station (Finch *et al.* 1996). Other recent work focusing on the strategic long term modelling of pest risk (Shirley *et al.*, 1999), in that case relating to indigenous slug damage to arable crops, is similarly point-based in its weather simulation approach. Warnings to take management action produced by agricultural consultancies (e.g. ADAS) are commonly based on a limited set of point model results run at the locations where input data are available, even where these are constructed within a GIS environment (e.g. Parker and Turner 1996). The potential impact of this approach on the advice given however appears not to have been quantified to date, although a number of papers have attributed poor field validations of models satisfactory in the laboratory to a lack of locally relevant input data (e.g. Higley *et al.* 1986). The working hypothesis for this section is that significantly improved timings of control actions in both time and space may be achieved through the linking of spatially referenced temperature data with applied pest phenology models.

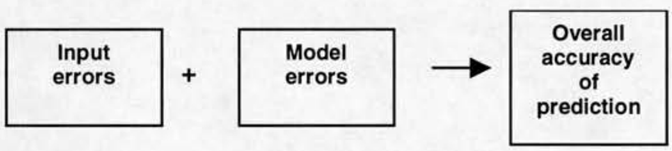


Figure 7-12. Error sources

Accuracies of the limited numbers of spatial phenologies (e.g. Schaub *et al.* 1995b, Régnière 1996) have previously been reported in terms of their *overall* error (Figure 7-12). In an applied setting, this combined figure provides the required assessment of a model's 'fitness for purpose'. However, at a more theoretical level the measure does not help assess the relative contributions of the individual components to overall accuracies, and obscures the particular effect of using interpolated rather than nearest neighbour input data. Instead, and in keeping with the previous chapters, this work uses cross-validated temperature estimates to model phenologies, which as Figure 3-17 (p117) demonstrated may then themselves be regarded as cross-validated model results. In this manner input temperature data are subjected to geographical uncertainties, but the phenology model used is regarded for the purpose of the exercise as without error: variations may be attributed to input data methodology alone, as required.

Research issues relating to the use of geographically referenced pest phenology for integrated pest management that have been identified within the literature (Chapters 1 and 2) and that are to be addressed within this section are summarised as follows:

- Phenology models are increasingly being used to target the timing of pest control options, for both economic and environmental reasons, but attention has so far been paid to the temporal aspects of pest development at the expense of the geographical;

•Models running on the basis of daily temperature data, most commonly use inputs from the nearest meteorological station. In many cases this may be remote from the location at which phenologies are being estimated. The associated errors in these estimates of temperature are thought by many to be high, but remain unquantified;

•Where geographical phenologies have been computed, these have largely been produced by interpolating model results at a limited number of points, rather than by running a model 'across the landscape' using spatially distributed input data;

•Geographical phenologies have previously been computed using simple interpolation algorithms only, with no consideration of more sophisticated alternatives that make better use of spatial autocorrelation;

•Previous geographical phenologies have been assessed by means of sparse insect trap findings. The error measured is therefore a combination of that resulting from remote input data and the biological model itself. This provides a 'fitness for purpose' assessment for applied biologists, but constrains understanding of error propagation to those stages of insect development most easily observed in the field;

•The effectiveness of using geographically referenced input data (daily maximum and minimum temperatures) as opposed to remote point-based data at meteorological sites for IPM has not previously been assessed;

•The latest breed of agricultural decision support systems (e.g. DESSAC, MORPH) contain many models requiring daily temperature inputs. There appears to be considerable scope for exploring how targeting might be improved in both space and time together in order to improve the effectiveness of these tools in practice.

7.2.2 Methodology

7.2.2.1 Modelling framework

In order to provide focus, results for a single pest (codling moth, *Cydia pomonella*) are presented within this section. As discussed within Chapter 2 (Section 2.1.1, p31), codling moth is one of the three major pests encountered by apple and pear growers in south east England (Morgan and Soloman, 1993) and presents an on-going threat to apple production in England and Wales. The choice of this pest is also representative of those whose control options have been tackled within agricultural decision support systems. Some of the earliest computerised systems, such as PETE (Welch *et. al.*, 1978) or in a British context, the PESTMAN suite (Morgan and Soloman 1993), were designed to tackle this pest among others. The phenology model incorporated within the PESTMAN system is used within this section, the biological characteristics of which were discussed within Section 3.1.3 (p76).

In keeping with Chapter 5 onwards, partial thin plate spline interpolation of daily maximum and minimum temperatures was used to compute both gridded phenologies and cross-validated error estimates for multiple stages within the lifecycle. As has been reported within Chapter 6, the temperature approach has certain advantages in terms of maintaining appropriate models of spatial correlation whatever the level of disaggregation in phenologies and reducing the chance of logical error both within stages in terms of date range and also between stages. As with the Colorado beetle experiments (Section 7.1), the model runs were initialised with a nominal number of overwintered pests in pupal stage at the beginning of the year for each grid square. Diapause is broken as a result of increasing day length and temperatures. Since the results provide an indication only of the timing of pest activity and not the size of the infestation, output data are generally expressed as the dates on which critical phases of the lifecycle (specified by stage and percentage emergence) are reached.

Given the focus on decision support systems for short and medium term pest management, rather than long-term risk as within Section 7.1, the majority of results are presented in relation to one year (1976). This internal consistency of reporting year between chapters allows the distribution of accuracies reported for the interpolated temperatures (Section 4.1.4, p153) to be considered in relation to the accuracy of the codling moth phenologies. The volume of data used (174 meteorological sites) reflects typical levels of synoptic data that, owing to its automatic transmission, are most commonly used for agricultural applications.

7.2.2.2 Experiments

In order to increase the generality of the results and build a broader case for the use of interpolated temperature data, the relative benefits of input data computed using nearest neighbour versus partial thin plate splines were explored for each stage in the codling moth's development (50% emergence). While control measures are most commonly applied against eggs or larvae the particular targets will vary according both to pest lifecycle and chemical used, and many models may use additional biofix data such as first adult or date of maximum adults.

The geographical phenology-modelling framework was used to estimate the date at which critical developmental thresholds were reached for the years 1976 and 1986 to a $1km^2$ grid throughout England and Wales. Results, referred to as 'fully spatial' phenologies, were computed using both spline and Voronoi interpolation techniques, the Voronoi polygons representing the most commonly used 'nearest neighbour' technique implicit within the practical application of insect phenology models. These were imported into a proprietary GIS for visualisation and analyses.

The basic questions investigated were:

- Do interpolated inputs improve over nearest neighbour results, on average?
- Is this pattern the same between different stages of development, and throughout the country?
- To what degree do the two methods of interpolation over- or under-perform at similar locations?

As in previous chapters, jack-knife cross-validation results formed the basis for assessing the relative accuracies between methods and exploring their geographical pattern. Residual errors in the Julian dates predicted were computed for 50% emergence of each major stage of development of the codling moth (adult, egg, larva, pupa: Section 2.1.1, p31) and summarised using the r.m.s. statistic to provide an aggregated indication of interpolator performance over the country.

Conventional wisdom amongst applied entomologists suggests that there is little benefit from interpolation in predominantly flat agricultural areas (e.g. East Anglia). This is explored by assessing the size of absolute residual error (measured in days) achieved at the same point locations over England and Wales by using Voronoi and spline techniques. The average degree to which errors derived using the spline method exceeded those of the Voronoi, and vice versa, was computed. Additionally, locations at which Voronoi results performed better than the spline method according to the point-based cross-validation results were plotted over England and Wales for each stage of development.

7.2.3 Results

7.2.3.1 Gridded outputs

Gridded results of the dates at which 50% emergence is expected at the adult, egg and larval life stages for the first generation codling moth in 1976 are shown in Figure 7-13. Results for 1st generation pupae and 2nd generation adults and larvae are plotted within Figure 7-14. That England and Wales lie at the margins for codling moth development is clearly illustrated within the plots for this particularly warm and therefore favourable year for pest development. The completion of one generation is not feasible on the basis of temperature within the highest upland areas (Figure 7-14a), while a second generation of larvae is confined predominantly within the south-east. In terms of overall variation over space per stage, differences of 174 days are seen within plots for 1st generation pupae and 130 days for 2nd generation adults. This contrasts with a range of approximately 50 days in the emergence dates for 1st generation adults and eggs.

Estimates of development based upon actual temperature data are shown in conjunction with the spline surfaces (Figure 7-13 and Figure 7-14) as point results using the same legend scale for reference, and their aggregate distribution will be discussed further in relation to corresponding Voronoi polygon results and their 'fitness for purpose' within the next section. In terms of their general variation, results for 1st generation larvae are similar to those for accumulated temperatures (Section 5.3.1, p181). For 1st generation adults however, errors at coastal sites such as Gwennap Head, Mumbles Head, Isle of Portland are further emphasised.

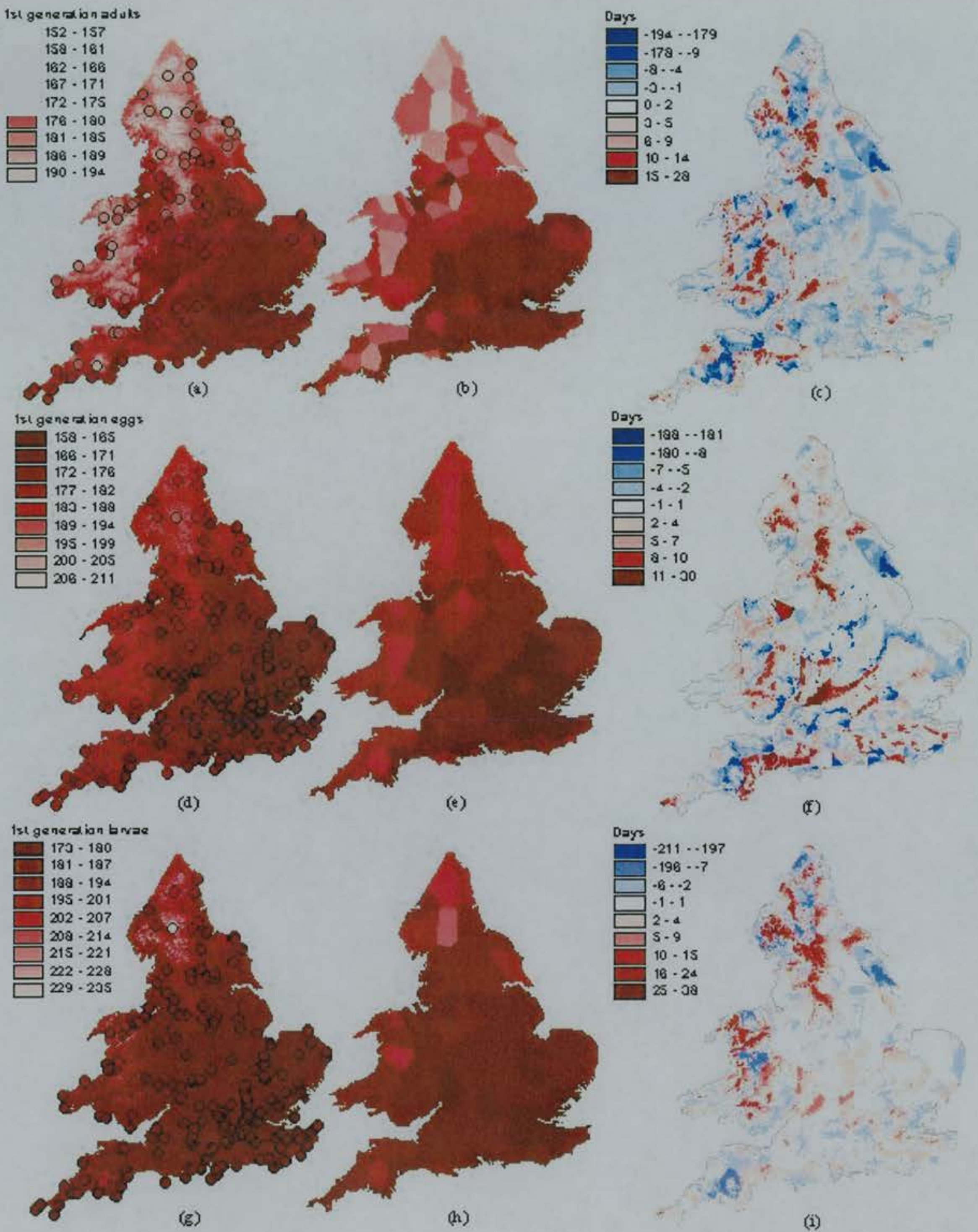


Figure 7-13. Emergence dates for fully spatial codling moth phenologies (a,d,g), nearest neighbour phenologies (b,e,h) and the standard deviation of their difference for 1st generation emergent adults, eggs and larvae (50% development), 1976

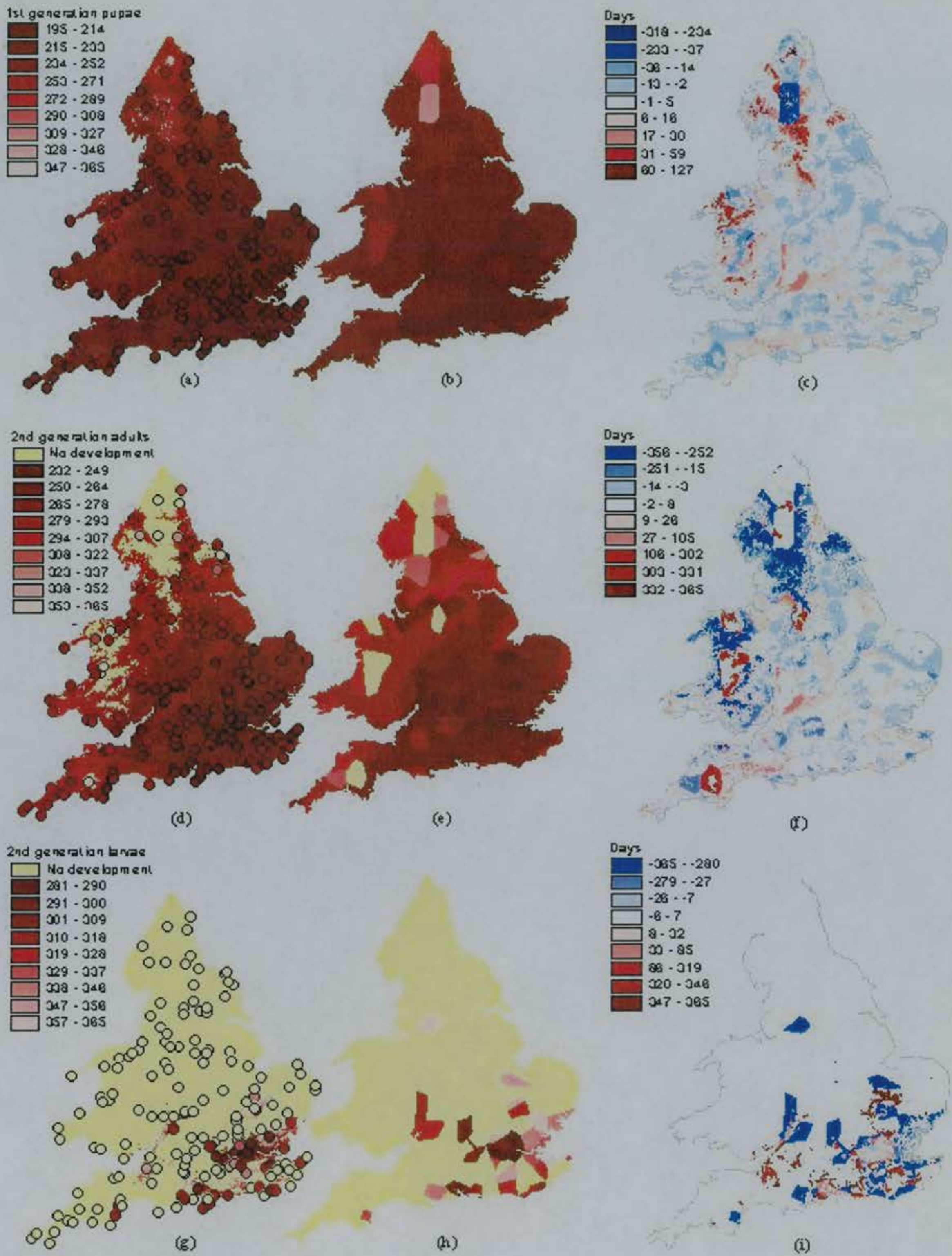


Figure 7-14. Emergence dates for fully spatial codling moth phenologies (a,d,g), nearest neighbour phenologies (b,e,h) and the standard deviation of their difference (c,f,i) for 1st generation pupae and 2nd generations adults and larvae (50% development), 1976

While the general pattern between Voronoi and spline based images is similar, differences are most manifest within upland areas containing little meteorological data such as the Lake District and Pennines, where the Voronoi estimates tend to overestimate emergence dates relative to the spline-based results (Figure 7-13c,f,i). At locations where data is located preferentially in upland areas however, this situation is reversed such as at Widdybank Fell and North Hessary Tor (Figure 7-14). Analysis of the difference in location of the cross-validated estimates between techniques confirms this visual impression. Particularly significant are the variations Figure 7-14(g,h) relating to areas of Kent and the Severn estuary, strongly associated with commercial apple growing. For Kent, a large swathe of the Voronoi results indicates no development while for Gloucestershire the reverse situation is indicated using nearest neighbour approaches with more subtle variations revealed within the spline plots. In terms of absolute difference, emergence dates for 2nd generation larvae are on average 11 days earlier than those computed by spline techniques. This general tendency for Voronoi to suggest earlier emergence dates is illustrated over all developmental stages (predominantly 'blue' areas).

7.2.3.2 Splines vs. voronoi: Comparative errors

Figure 7-15 provides a measure of the relative success between partial thin plate spline interpolation used for this study and the 'nearest neighbour' techniques that are de-facto in a British context.

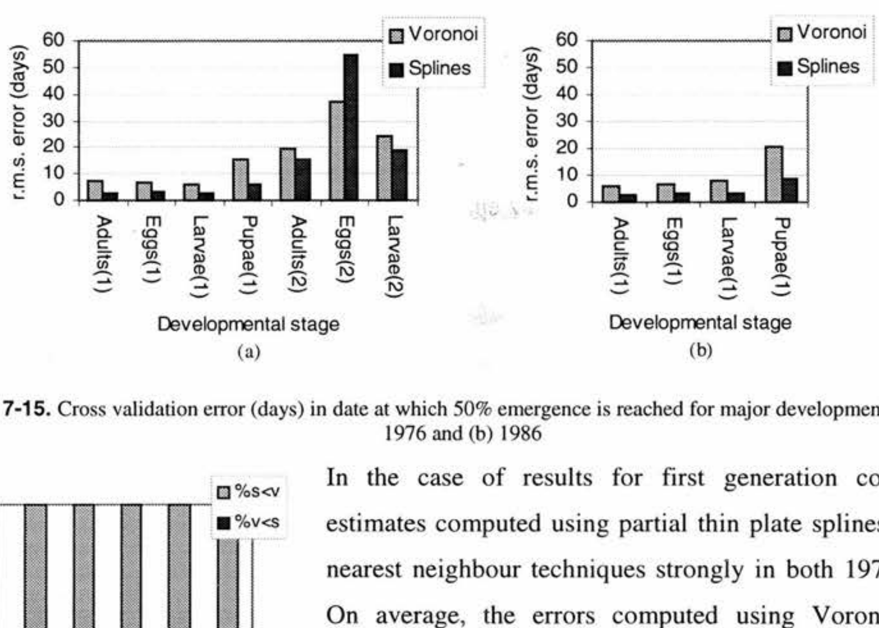


Figure 7-15. Cross validation error (days) in date at which 50% emergence is reached for major developmental stages, (a) 1976 and (b) 1986

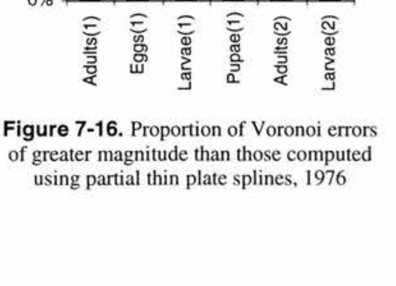


Figure 7-16. Proportion of Voronoi errors of greater magnitude than those computed using partial thin plate splines, 1976

In the case of results for first generation codling moth, estimates computed using partial thin plate splines outperform nearest neighbour techniques strongly in both 1976 and 1986. On average, the errors computed using Voronoi polygons exceed double that of the interpolated method. While the overall proportion of occasions where spline errors are below those for Voronoi at any one site falls as the model run progresses, even for 2nd generation larvae a majority of sites benefit from the full interpolation approach (Figure 7-15(a)). In 1986, this 2nd generation is unable to develop to the damage causing larval stage.

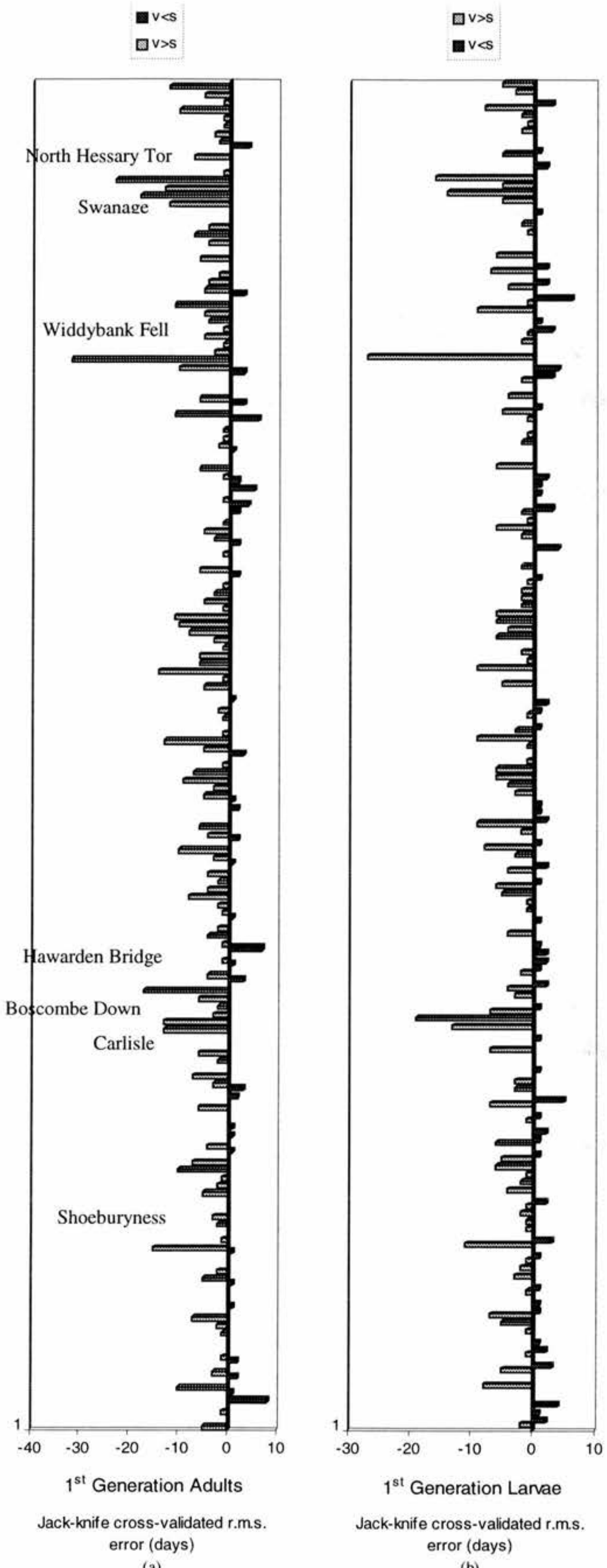


Figure 7-17

In part, the high accuracy levels for 2nd generation egg emergence dates may be attributed to the effects of calendar date. As Figure 7-14 demonstrated, this stage of development is not reached over approximately one third of the country. Where development occurs on the basis of known temperature but not using the interpolated estimates, or vice versa, error in date terms will be recorded as 365. Adjusting the figures to remove these errors of omission or commission and focus on dates should the event occur reduces both the spline and Voronoi error to an average of 2.5 days.

While average figures provide an overall measure of the relative efficiencies between methods, investigating their underlying variability is also worthy of investigation. Figure 7-16 identifies that, across all developmental stages, the average proportion of locations throughout the landscape at which errors are reduced through the use of partial thin plate spline methods is 70%. Results relating to individual sites are shown for 1st generation adults and larvae within Figure 7-17 to show the distribution of this effect. Data plotted relates to the absolute value of the spline r.m.s. error minus the corresponding value computed using Voronoi polygons. Extremes follow a mixture of highest cross-validation errors resulting from Voronoi and spline methods. The highest values, located at Widdybank Fell and North Hessary Tor in both cases (Figure 7-17a,b) relate to extreme over-predictions in emergence date when using Voronoi polygons to represent sites at high elevations in areas of sparse data. Shoeburyness, Boscombe Down and Swanage also represent locations with extreme Voronoi error at coastal sites. The locations of these relative absolute errors are plotted within Figure 7-18, which provides a spatially referenced view of Figure 7-17 through each stage of the 1st generation codling moth development.

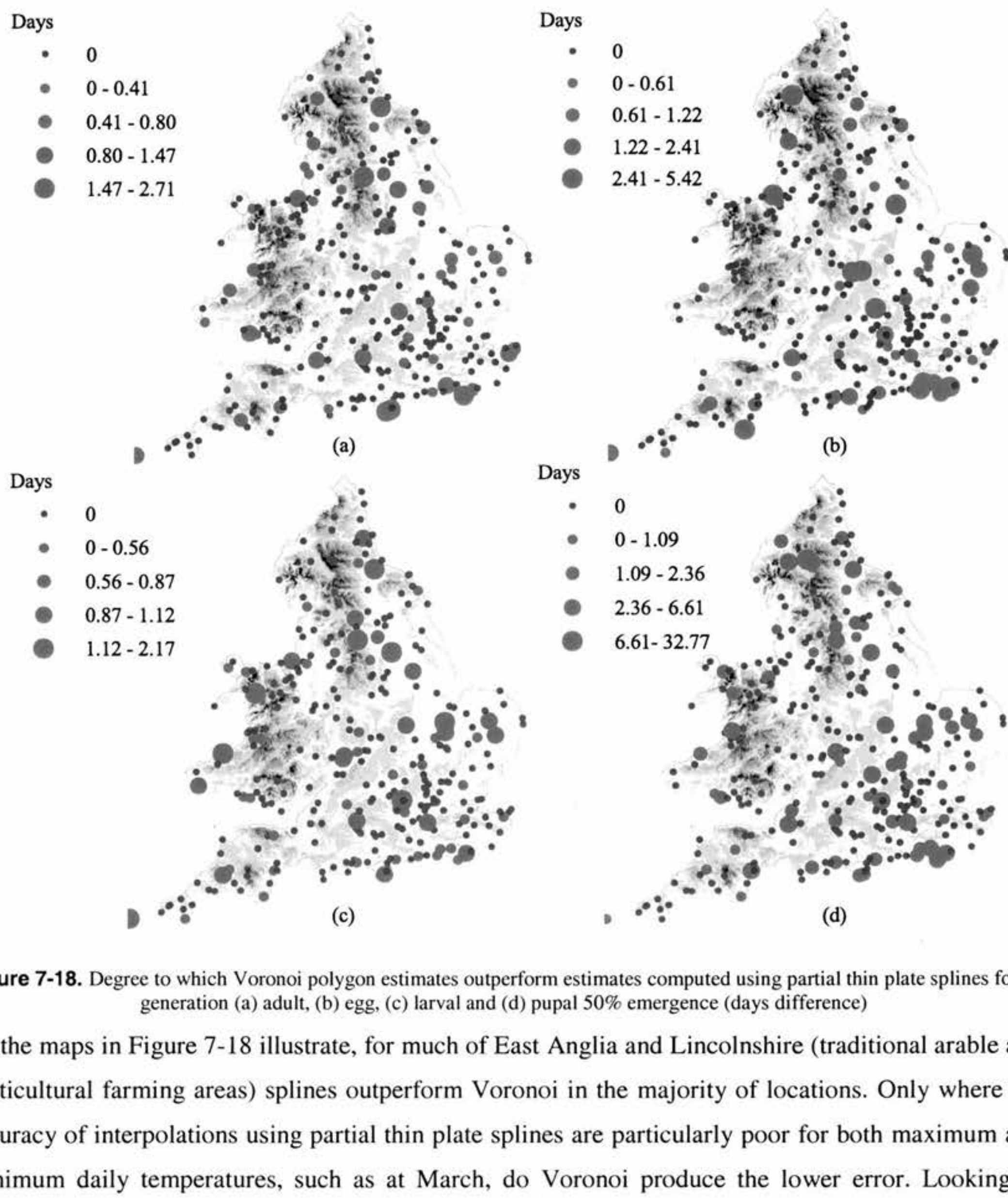


Figure 7-18. Degree to which Voronoi polygon estimates outperform estimates computed using partial thin plate splines for 1st generation (a) adult, (b) egg, (c) larval and (d) pupal 50% emergence (days difference)

As the maps in Figure 7-18 illustrate, for much of East Anglia and Lincolnshire (traditional arable and horticultural farming areas) splines outperform Voronoi in the majority of locations. Only where the accuracy of interpolations using partial thin plate splines are particularly poor for both maximum and minimum daily temperatures, such as at March, do Voronoi produce the lower error. Looking to commercial apple growing centres in particular, this situation is rather more mixed at the crucial larval stage in Kent with differential errors of up to 5-6 days (Figure 7-18c). Within Gloucestershire, however, the splines perform relatively well. There appears to be no significant relationship between elevation and interpolator performance, as anticipated. Although Voronoi polygons do not generally perform better than interpolation (Figure 7-15, Figure 7-16), the analysis has revealed that this does not hold in all cases and that there is no clear spatial pattern that would allow the generalisation of these results to specific locations *apriori*. The fact that the distribution of errors for codling moth differs to a degree from that for accumulated temperature given identical input data, and also between years, tells us that the errors are a complex function of model structure and the underlying temperature predictions. This empirical examination in which the locations where splines perform poorly relatively to Voronoi polygons is nevertheless potentially of applied biological significance given the original contention that Voronoi perform well in flat, lowland agricultural areas.

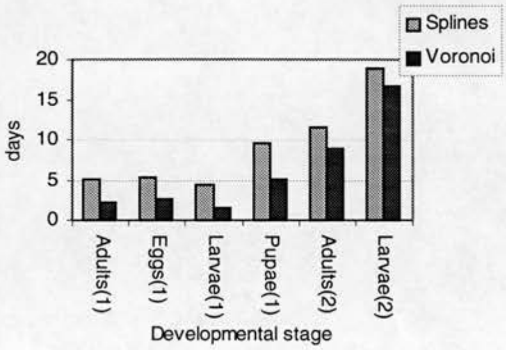


Figure 7-19. Difference in absolute error between Voronoi and partial thin plate spline results, 1976

Taking a stance from decision theory to quantify further the relative merits between the techniques, the average magnitude with which errors using Voronoi interpolation exceed those of splines are illustrated within Figure 7-19. This illustrates the average difference in absolute residuals between the Voronoi and spline methods, divided according to the method that shows best results. The penalties of choosing partial thin plate spline interpolation over Voronoi at a location where they prove to be less accurate are considerably smaller (14% of value estimated using actual temperatures, on average) for those of the reverse situation when choosing Voronoi in preference to better-performing splines (33% of value estimated using actual temperatures, on average). In keeping with the previous figures, these margins are slimmer for the 2nd generation. Overall, this suggests that there is little to be lost and much to be gained by adopting the partial thin plate spline interpolation approach for providing locally relevant temperature input data for this phenological model.

7.2.4 Discussion

7.2.4.1 Nearest neighbours: a farmer's best friend?

The aggregate halving of accuracies across all 1st generation developmental stages when using partial thin plate spline interpolations in comparison to nearest neighbour techniques for codling moth has considerable applied biological significance. While much effort and investment is currently being applied to improving the underlying phenology models within complementary research projects, these results suggest that previous applied entomologies have focused on the biological modelling at the expense of considerations regarding input data. The use of spatially relevant input data rather than 'nearest neighbour' meteorological information from the synoptic network, even at the relatively crude 1km^2 resolution used in relation to insect habitat, has scope to improve the field performance of well calibrated phenology models. Falconer (1998) comments that while producer interest in low input farming appears to be growing, the site-specificity of changes in practice and the absence of 'blueprints' makes it difficult for advisors even where models are collected together under a cohesive interface. Advice given by agricultural DSS may not encourage cost-minimising abatement strategies unless considered locally relevant, and may as a result be used selectively by recipients. This work presents a step in the direction towards more confident pest management advice, where individual control practices are *'increasingly used as a stiletto instead of a scythe'* (Van Emden and Peakall, 1996, p4) in *both* a spatial and temporal sense within an integrated framework. In turn, this may assist in the reduction of chemical usage with its environmental and economic concerns. Currently, the implementation of integrated techniques on a commercial basis is still at low levels (Curry 1997).

While partial thin plate splines are not universally optimal, the penalty for their use is slim relative to the use of 'nearest neighbour' techniques. Where temperature estimates are poorest however, nearest neighbour techniques produced lower errors, pointing to the benefits of using a more sophisticated approach to the interpolation of daily temperatures than in the limited previous studies (Russo *et al.* 1993). This does not necessarily occur in flat agricultural land, as has previously been assumed. These precision and error issues have rarely been touched upon previously within the context of insect ecology.

Both absolute and relative errors contribute to an assessment of whether a modelling system is fit for the purpose it is intended. The number of days within which an estimate must be bounded will vary according to the efficacy of the control method used and the prevailing weather conditions in particular. Many pesticides come with standard instructions not to re-spray within seven days. This suggests that the effectiveness of the chemical will have decayed considerably within that period such that re-application might be necessary for estimates with error bounds outside this range, the very situation the phenology models are designed to avoid. Increased accuracies in phenological information are especially important for the biological control agents because of their relatively shorter persistence and higher product price, as Blago and de Barardinis (1991) comment in regard to the use of *B. thuringiensis* against codling moth. On this basis, even improvements of 2-3 days in estimated emergence dates might provide practical control benefits. In the majority of areas and for all developmental stages, this is exceeded.

Consideration of both developmental profiles and space-time plots suggest that variation over time in codling moth phenology is dominant in relation to variation in space, but that this varies with developmental stage. This confirms a need for the continued development of temporally sophisticated phenology models. The practice of estimating dates of pest emergence by reference to those observed within more southerly or lower lying neighbourhoods, as is often practised, is confirmed in all but areas marginal to pest development. The value of the geographical phenology approach is greatest when viewed as a precursor to more sophisticated modelling of pest populations in relation to local crop and harvesting schedules, where relationships are likely to be less geographically static and for which location provides the essential axis on which integration between agricultural elements may be made.

The results within this section are presented as a case study for codling moth. This pest is put forward simply as a 'representative' indigenous species, the model used reflecting a typical non-linear phenology modelling approach common within current agricultural DSS. Since apples are grown commercially only in limited areas, some licence is required to consider data from England and Wales as a whole, although their domestic range is wider. However, associated figures for Colorado beetle and accumulated temperatures (Figure 6-5) show a similar trend, suggesting the broad generality of the findings for a variety of both complex and simple insect phenology models.

7.2.4.2 Phenological framework

The ability to model geographical phenologies as a function of spatial input data rather than interpolated model results (Chapter 6) was fundamental in exploring the propagation of errors arising as a result of scattered and often remote temperature input data. The value of the jack-knife cross-validation approach taken to propagate error, unique within a geographical setting to this work, is that it provides a means of deliberately separating input errors from those arising through other sources of uncertainty. Previously, uncertainties within individual sub-components have been masked. Others have chosen to validate spatial phenologies on the basis of limited trap catches, which provides a vital practical test of usability (Worner 1992, Pruess 1983) but that in theoretical terms has restricted exploration of the case for spatially relevant input data (e.g. Schaub *et al.* 1995b). While the results support Higley *et al.*'s (1986) suggestion that the use of spatially limited temperature data is one of the most important sources of error in degree day models, rather than model deficiencies per se, they do not confirm the case. Examining the biological modelling error *together* with input error to identify the relative size of contribution between the two major contributors to overall uncertainty will be an important next step in the research process, requiring stochastic rather than deterministic phenology models (e.g. Finch *et al.* 1996).

Many of the more general benefits of the geographical modelling approach taken within this study in relation to non-indigenous pests have been discussed within Chapter 5 (Section 5.1). Firstly, the 'fully spatial' nature of the outputs provides a richness of information in comparison with the point-based advice traditionally provided in a British context (e.g. ADAS advice bulletins, Parker and Turner 1996, Finch *et al.* 1996). In comparison with recent Europe work, the 1km^2 resolution of fully spatial phenologies exceeds that of results aggregated to regions or crude grids (e.g. Pl@ntInfo, Figure 5-x). While geographical phenologies of indigenous pests have been demonstrated for local regions by Régnière and Schaub (Régnière 1996, Schaub *et al.* 1995b), national coverage at this scale is rare. Weekly updates by the Meteorological Service within the MORECS scheme are for example currently provided at 40km^2 resolution (Hough and Jones 1997). Additionally, unlike work within a North American setting, outputs from the exploratory modelling framework may be presented as traditional, temporal graphs of phenological development at any given point in the landscape rather than at recording sites only. This work combines elements of these previous studies, not combined previously.

As for the treatment of non-indigenous pests within this thesis, emphasis has been placed at this stage upon modelling the timing of developmental stages (*phenological* modelling), not the absolute numbers of pests expected (*population* modelling). Similar caveats relating to the multiplicity of factors affecting insect populations apply. Within the context of indigenous pests, a number of future possibilities arise from the framework developed as explored within Chapter 6.

7.2.4.3 Strategic issues

The increasing popularity of on-farm weather recorders provides some indication of the value attributed to the latest pest and disease phenology models for more focused control solutions, and may be especially cost effective for larger growers. Where these data are available, it is likely that they will produce improved results over the interpolated values. This is however subject to caveats regarding the exposure of the sensor. Phelps *et al.* (1993) suggest in a British context that, to be of practical use, phenological models must be capable of using standard UKMO meteorological data. In this sense local variations in temperature and therefore phenology are bound within the model calibration process, and models run using data from different exposures may prove unsatisfactory.

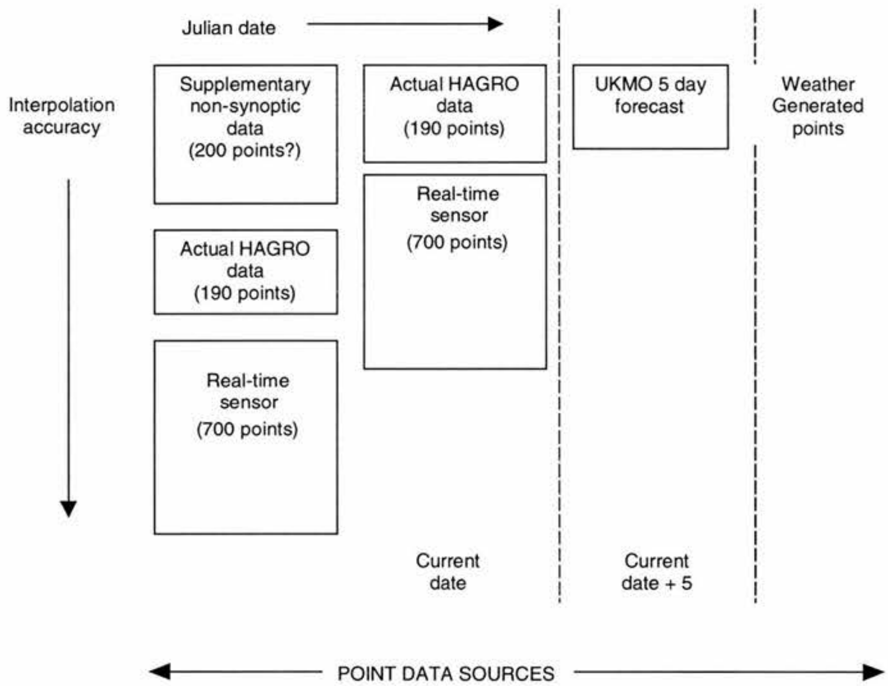


Figure 7-20. Data volumes, by time scale of transmission

For the agricultural advisor running phenological models for a number of scattered locations on behalf of growers, use of interpolated temperature data without the associated data collection, formatting, testing and exposure issues related to multiple sensor types is likely to be attractive. Whatever the base data, locally relevant interpolated data from appropriately merged networks would provide a uniform base upon which decisions may be made. Additionally, the availability of national or regional interpolated inputs allows the development of multi-scale models where local processes may be triggered on the basis of regional information, for example aphid dispersal rates and the transmission of diseases such as barley yellow dwarf virus (BYDV) (Walters, pers. comm.).

Results for this section are based upon data from an approximation to the UKMO synoptic network throughout England and Wales. These therefore reflect the type of accuracies currently feasible for 'real-time' agricultural application. As Figure 7-20 shows, this reflects a mid-point in the overall availability sequence of input data volumes available for daily temperature within Britain when setting the work within a more pragmatic context. Régnière's (1996) work, which complements this study through its practical rather than theoretical focus, for example took into account the strategic requirements for agricultural advisors to address the longer term 'what if' question through the incorporation of a spatio-temporal weather generator. In meeting the goal of this thesis, to explore space-time patterns in insect phenologies, archived data was sufficient.

While temperature sensors are relatively affordable, more complex recording stations measuring for example relative humidity and rainfall in addition remain the province of the large grower rather than the individual farmer. Many potential users of decision support systems will not have a comprehensive 'on-farm' automatic weather station, and those that do may not operate independent software to compute estimates of derived inputs such as evapotranspiration or solar radiation. The range of models within the agricultural/horticultural arena literature is diverse, and the interests of those visiting early seminars of the DESSAC consortium[1] for example suggests considerable need for a greater variety of geographically referenced driving variables ranging across both air and soil environments (Appendix 12). Similarly to the case with temperatures discussed within this work, the most common form in which inputs such as soil moisture, evapotranspiration, daily maximum and minimum temperatures are available to decision support developers or applied researchers is at a limited number of historically-determined sample points. Many of these variables have not been interpolated extensively at a national level, especially on a daily basis at locally relevant scales and using the more advanced interpolation techniques afforded by GEO-BUG. In exploring the limits to scale afforded by the extended data set, together with alternative structures for interpolation (see neural networks below) and appropriate topo-climatic considerations lie many possibilities for future work. The incorporation of remotely sensed imagery, for example radar rainfall estimates or ground sensed temperatures, is likely to be increasingly important. However, designers of decision support systems need to hide the details surrounding the provision of such model input data from their users if they are to become an efficient tool within the workplace.

The volume of data available through the standard UK Meteorological Office network in 'real time' (HAGRO data) relative to the overall network is limited (Figure 7-20), and practical experience suggests that .the scope for interpolating other variables such as rainfall may consequently be

[1] Dessac Workshops, 'Dealing with uncertainty in agricultural and horticultural decision support systems' October 1996, 'Symposium on decision support systems for agriculture and horticulture' April 1996. Silsoe Research Institute

constrained. In order to achieve the timely delivery of detailed agro-meteorological requirements, it is likely that the merging of additional sensor data will be needed although the limits to the scale achievable have yet to be explored. The integration of additional networks, for example those networks used in assessing road conditions or local co-operative data in conjunction with UKNO synoptic data, may be one means by which advances in representative provision may be made. Detailed consideration of how networks with their different site characteristics may best be merged is a current research topic of relevance to the agro-meteorological domain (e.g. Brown, 1996).

The multitude of variables required by the current breed of support systems extend beyond those traditionally provide by one institution, such as the UK Meteorological Office. In a British context, there is currently no one place where spatially referenced meteorological and soil related data are consistently collated and updated at scales appropriate in both the temporal and spatial dimension for the current breed of agricultural decision support systems. Bringing together the base data and means with which to provide representative model inputs at scales appropriate in space and time may form one element of the solution. The computational overhead in creating such estimates may however be considerable where sophisticated algorithms are required, both in terms of the volumes of data to be stored and processing time. This points to the use of a central service provider, processing and disseminating requests for model input data from users. The use of telemetrics for distributing point weather data for agricultural/horticultural modelling purposes is particularly well developed in Scandinavia (Magnus et al 1993) and Germany (e.g. Kleinhenz et al 1996). In the majority of those cases however raw data is communicated with minimal processing, while the mode of communication is by fax or e-mail. Developments in spatial data handling using the World Wide Web make an Internet service a more modern solution for a query and distribution function for interpolated data. Research issues arise from the management of server scheduling and the design of an interface to assist users in extracting the relevant spatio-temporal information. Additionally, cartographic communication using the Internet provides a visual and interactive means of educating the potential user community on advances in and advantages of agricultural/horticultural models and the scale limitations of spatially referenced data.

This thesis focused on the static, landscape wide mesoscale, and practical agricultural applications rather than insect ecological research. While there has been much progress in dispersion modelling, current simulations of insect movement and population growth tend to deal with only a few of the possible controlling factors such as field size, crop life cycles, control environment and planting patterns, genetic drift or changes in insect life cycle within one model. Farmland ecology, which needs to be better understood for sustainable agriculture to be achieved, is however much more complex than this, involving heterogeneous landscapes changing over time, and populations developing under dynamic predator-prey relationships. Rarely is interaction modelled in 'geographical' space, as distinct from spatially (homogeneous or regularised environments). In part this relies on biologists data on movement under different conditions and intensive sampling data. From a GIS perspective however, there are few simulation environments capable of providing a space-time framework for such a task should the biological research move forward. Insect dispersion modelling is a multi-stranded topic; more realistic models need to incorporate non-stationary processes in time and space to account, for example, for interactions between landscape and phenology, for pest/predator competition and genetic mutation. In most studies of dispersion using cellular automata, only one 'agent' has been considered to be dynamically changing over time. Usually this is the insect population. From a technical viewpoint, the scope for increasing the complexity of modelling by incorporating multiple explanatory factors using the current approaches (partial differential equations and cellular automata) appears limited and an agent based strategy (Westervelt and Hopkins 1999) may be preferable. The continuous maps of meteorological conditions produced by this thesis would require re-scaling with land-cover data and micro-habitat effects at a highly localised scale, using networks of temperature sensors and these serve as inputs to crop and phenology models.

7.2.5 Summary

- The assessment of error in insect phenology timing relating solely to remotely sited input data has not previously been assessed;
- The propagation of cross-validated estimates of temperature through the phenology model provides a novel means of quantifying the effect of input data configuration on phenological results;
- Use of weather data from the nearest UK Meteorological data station (174 points) for phenological modelling gives, on average for mainland England and Wales, double the error of that using partial thin plate spline interpolations;
- Spline interpolations provide improved phenology results over nearest neighbour techniques for 70 % of locations over England and Wales, taking all developmental stages into account;
- Nearest neighbour techniques do not necessarily perform well in agricultural lowland areas, as commonly assumed by applied insect ecologists;
- Where nearest neighbour strategies perform best the margin of improvement is on average 14%, while where splines perform well their accuracies exceed those of Voronoi techniques by the wider margin of 33 %;
- In relation to previous work presenting geographical phenologies for indigenous pest management in a European setting, the spatial resolution achieved is relatively fine (1km^2) and the ability to plot the temporal phenology series at any point on the landscape has not been attempted previously;
- Considerable opportunity lies in addressing issues relating to:
    - The assessment of the overall error in the geographical phenologies to validate their 'fitness for purpose', through the use of trap samples;
    - The spatio-temporal derivation of additional agricultural/horticultural model input variables, for which the volume of data available for this thesis was insufficient to model spatial autocorrelation adequately;

- Their communication to users of decision support systems by means of the Internet;
- Dynamic rather than static modelling of insect populations, which would require inter-disciplinary research teams to develop both insect behaviour and micro-climatic aspects of the work.

8 Conclusions

8.0 Introduction

Within the context of the needs of the agricultural/horticultural communities for improved risk assessments, and particularly for more precise information on where a pest may thrive in time and space, the thesis has explored geographical insect phenologies throughout England and Wales at a grid resolution of 1km^2 for the first time. In building a prototype system for use in exploring geographical phenologies, a number of research questions were outlined for consideration (Section 1.5). This chapter begins with conclusions structured as short answers to these specific points (Section 8.1).

The chapter then works outwards from this position to supplement the conclusions with the consideration of a number of additional findings resulting from the research process (Section 8.2). Firstly, the contributions to knowledge made in the field of geographic information science are outlined, and secondly the understanding gained of geographical aspects of insect phenology is summarised. As with all research projects, any study has its limitations. Burrough (1992), listing a number of means to improve the quality of modelling results, included the development of better methods and models, more data, different data, better calibration and better resolution. The suggestions for further improvements to this work, which will be included within these concluding remarks, will cover many of these issues. The chapter closes by suggesting a number of future work opportunities arising out of the project relating both to insect ecology and GIScience (Section 8.3).

8.1 Summary conclusions

Basic science

- *How may the primary inputs to phenological models, the observations at meteorological stations of daily maximum and minimum temperatures, be estimated continuously over extensive and diverse areas?*

Daily maximum and minimum temperatures were interpolated over England and Wales at a resolution of 1km^2 using partial thin plate splines in conjunction with selected topo-climatic guiding variables. Annual average r.m.s. errors were 0.8°C and 1.14°C respectively. These errors are slightly improved over those reported in the recent literature. Given the spatial resolution of the study (1km^2), a degree of variation as a result of micro-climatic processes will always be expected and the accuracies achieved may be close to their limits.

- *To what extent does the choice between method of interpolation produce differences in the magnitude and distribution of the input conditions for modelling?*

No significant differences were encountered between the accuracies achieved using partial thin plate splines, automatic inverse distance weighting and de-trended ordinary kriging although the more sophisticated interpolators required fewer covariates to achieve similar accuracies. Trend surface analysis, however, (the choice in previous work on geographical phenologies) performed significantly poorer.

- *How does the spatial location of the available meteorological data through the validity of the interpolators used influence the magnitude and distribution of uncertainties in the nation-wide estimation procedures?*

Accuracies were poorest in upland areas with sparse data, and at coastal stations on exposed cliff sites. The prediction of temperatures in urban areas was significantly improved in comparison with previous studies. High errors in biological model results were found predominantly at locations where *both* maximum and minimum temperatures were estimated poorly, but showed greater similarity with sites of poor accuracy of prediction in minimum temperature. The calibration of interpolation parameters for kriging and IDW would be improved with extra data from meteorological stations, especially for short lag separations.

Exploration

- *Does the fully spatial method reveal significant differences in timing in comparison with the traditional nearest point method?*

Model accuracies computed using interpolated temperatures derived using the partial thin plate spline method were on average *double* those achieved on the basis of nearest neighbour estimates. Nearest neighbour estimates rarely outperformed those computed using splines, and where this occurred the margin of difference was slim.

- *What difference does interpolating phenological model results or phenological model inputs make to the magnitude, distribution and timing of the areas estimated to be at risk?*

Interpolating model results, while computationally efficient, can lead to errors in the logical sequence of pest development. Additionally, interpolating model results can over-smooth the expected phenological surface. Little difference in average r.m.s. accuracies between the methods was however observed.

- *How does the time at which insects reach a certain stage in phenological development vary over space and throughout the year, and between years?*

Differences in phenology are more pronounced over time than space, both within and between seasons. Nevertheless, as indicated within chapters 5, differences in development times of up to a fortnight were encountered even over relatively local areas. The degree to which these differences are important will vary according to the biological or chemical control agent being used, but are potentially significant. The marked variations in development from year-to-year demonstrated within chapter 7 for Colorado beetle suggest that risk assessments based on 'average' climate may lead to the underestimation of long-term pest risk.

Assessment

- *What difference does adopting a geographical (fully spatial) approach make to quantitative assessments of risk for non-native pests?*

From year to year the geographical approach to pest risk assessment, applied to the lowland pest Colorado beetle, led to lower estimates of land at risk (14% area of England & Wales) than that computed on the basis of point statistics alone. There appears a strong possibility that point data may, through a lack of representativeness, lead to overstatement of risk. Estimating area at risk on the basis of the geographical phenologies, without modification for areas in which target crops are grown, similarly gives rise to estimates of the total area at risk.

- *How may we best assess the reliability of the resultant spatial phenologies?*

Spatial phenologies were assessed using jack-knife cross-validation. This provided a means of assessing the error propagated as a direct result of the remoteness of the input data, and through the entire lifecycle. Cross-validation allowed a measure of accuracy of the geographical phenologies to be assessed even where non-indigenous pests were concerned. Tests using independent data showed that jack-knife cross-validation provided a robust means of assessing error in modelled phenologies. Residual errors from interpolation should *not* be further interpolated to approximate an 'error surface'. It is important to note however that the overall uncertainty associated with the results extends beyond these error statistics to include both errors in the biological models themselves, the underlying geographical and meteorological data and the underlying modelling approach itself. Establishing methods for the efficient computation of fully spatial 'error surfaces' that incorporate both geographical and biological error through space and time is an important subject for future research in the GIScience community.

Implementation

- *Are existing data networks sufficient for this fully spatial approach?*

The successful modelling of parameters such as those of the variogram model for the majority of days in the year suggest that the meteorological data set used (174 points) was adequate for the study. However problems on a minority of dates (30%) suggest that an improved sample of data with more data at short lag distances in particular, together with an increased volume of data overall, might assist in improving overall accuracies given the national extent of the study. To extend the study to more detailed resolutions would however require additional meterological data at a variety of exposures that are excluded from the synoptic data set, together with additional digital geographical data at appropriate resolutions for soil, land cover and water flow.

- *Can the system be based upon a conventional GIS, or is an alternative structure required?*

Proprietary GIS currently lack the structures required to facilitate efficient environmental modelling in both time and space domains *together*. Their provision of sophisticated interpolation algorithms, with automatically adjusted parameters, is also poor. GIS provided an adjunct to a bespoke modelling system designed for the project, and was used for the analysis and display of results only. The custom built software, which incorporated public domain code from a variety of sources, allowed the handing of nationwide grids over annual model runs through the explicit separation of the tasks of building interpolation equations and computing the gridded estimates themselves.

- *Is the science and technology of geographical information handling sufficiently developed to support the creation of operational systems for pest risk assessment?*

GIScience provided the means to produce satisfactory accuracies when modelling geographical phenologies through the use of sophisticated interpolation methods. However, in order to compute fully spatial estimates of error within these spatial phenologies that incorporate a wider concept of uncertainty, further research is required regarding the combination and propagation or error from multiple sources over *both* space and time. Current work within the literature has focused on the spatial element alone.

8.2 Progress achieved

8.2.1 GIScience

8.2.1.1 Interpolation of daily maximum and minimum temperatures

A two-phase modelling approach was used in the interpolation process. The first phase involved the derivation of multiple gridded covariates derived from landscape factors likely to influence climate processes, and the selection of an efficient subset of these topoclimatic variables for the prediction of temperature using stepwise multiple linear regression. Gridded covariates were selected that were either most consistently significantly related with temperature over the year, or that on the basis of the strength of their relationship, were particularly significant under certain weather patterns. Covariates relating to coastal influences were particularly dominant in the final subset of variables selected, as was elevation and an index of urban conditions designed to reflect the 'heat island' effect. Previous British studies have failed to account for the importance of urban land use on minimum daily temperatures. While this methodology followed a similar approach to those of Lennon and Turner (1995) and Cornford (1997), it extends upon the findings in that the earlier work accounted only for relationships with monthly temperatures and terrain, and daily winter, minimum temperatures respectively. However, while linear regression techniques are standardly used within the literature for the selection of guiding variables, the cross-correlation, non-linearity and non-normality of data created theoretical problems with the linear regression technique in this case. This is particularly the case for selecting appropriate variables under high-pressure weather conditions. Use of an alternative method for variable selection that is not as susceptible to these problems, such as a neural network for example, is suggested as a possible means of 'de-trending' the data without these statistical assumptions and of better incorporating nominal information such weather classification.

Once the covariates were chosen, these continuous, gridded variables were used to guide four alternative mathematical interpolation methods (trend surface analysis, partial thin plate splines, inverse distance weighting and ordinary kriging). These techniques were used to produce the continuous gridded estimates of daily maximum and minimum temperatures. Rarely have the four interpolation techniques used in this work been compared, for temperatures or otherwise, and particularly in the context of an applied study. This attention to detail was considered necessary owing to the known sensitivity of insect models to their daily temperature inputs. Moreover, the literature suggests that only limited attempts have been made previously to attempt the interpolation of *daily* temperatures using partial thin plate splines (Laughlin *et al.* 1993) although the technique has been successfully used at other temporal scales (e.g. monthly). Dividing the interpolation process into these two elements, the selection of covariates and mathematical interpolation, forces a particular trend/covariance split on the interpolation problem that attempts to take consideration of meteorological processes into account. This improves upon the incorporation of standard trend models of geographical co-ordinates, followed by the consideration of covariance, as is often advocated as part of universal kriging (Deutsch & Journel 1992). Nevertheless, the design of an approach that is able to incorporate both components adaptively, and together rather than singly, within the interpolation process remains an important goal for further research. Accounting for temporal correlation between daily temperatures, and between maximum and minimum temperatures, is a further potential line of enquiry.

Parameters for the interpolation methods were fitted automatically using maximum likelihood and iterative least squares fitting techniques. For the majority of days over the annual period examined, the fitting of a variogram model to the daily data, the selection of the power parameter for the IDW method and the smoothing and roughness coefficients for the partial thin plate spline model were effective. The automation of this pre-processing of meteorological data for each interpolator was crucial given that the interpolator had to adapt to produce accurate surfaces for each day as inputs to phenology models run over an annual cycle. Such adaptivity in interpolators to daily data is unusual in such an applied study, and within the theoretical literature adaptive interpolation is still less common than the use of fixed parameters. Often, improvements to interpolation accuracy using automated parameters using one mathematical method are compared with those using static parameters selected on an ad-hoc basis or from limited trials.

Analysis of improvements in accuracies resulting from using increasing number of covariates to guide interpolation were made, with the residual errors in temperature estimation computed using jack-knife cross-validation at known data points. This indicated that, despite the *known* significance of the relationships between the gridded variables with temperature, improvements to accuracy became negligible when the number of covariates used was increased beyond 5 or 6. While partial thin plate splines performed best and trend surface analysis significantly poorest on the basis of residual range, bias and r.m.s. errors, differences between the three techniques were small. However, the more sophisticated interpolation techniques, splining in particular, required fewer guiding covariates to achieve similar accuracies to the simpler techniques. The conclusion that may be drawn from this is that the considered use of autocorrelation within the data provided an effective surrogate for otherwise more detailed modelling of atmospheric processes. Previous work developing geographical insect phenologies has unquestioningly used trend surfaces as the basis for interpolation, of temperature and model results. Trend surfaces performed poorly under certain weather types, although required less pre-processing of model parameters. This study concludes that, for the given volume and distribution of meteorological data available, splining is most efficient for the interpolation of daily maximum and minimum temperatures since it needs fewer covariates to achieve similar or better accuracies and is computationally swift. The findings suggest that Laslett's (1994) widely cited conclusion that splines never outperform kriging for irregular data should be more carefully interpreted as the result from a particular case study than as a benchmark position.

Errors in the interpolated temperature surfaces assessed using both jack-knife cross-validation and additional independent data were not necessarily coincident with areas where meteorological stations were sparse, and the pattern of the residuals varied over different dates. Poor estimates of maximum and minimum temperatures were associated largely with exposed coastal cliff sites and extreme upland sites for which lapse rates had largely been extrapolated owing to the greater availability of lowland data compared to that at higher elevations. The incorporation of terrain shape, for example using wavelet analysis, is one suggestion for improving the results in coastal areas that arise as a result of local situation. Ultimately, it is concluded that that such errors relate to micro-climatic influences below the resolution of the $1km^2$ grid of derived covariates. To account for processes operating at scales below $1km^2$, for example relating to land cover and soil type, would necessitate the incorporation of additional digital geographical data at appropriate resolutions and meteorological data at alternative exposures (site/aspects) to those meeting the standard synoptic UKMO guidelines.

In conclusion, there is a limit to the value of using increasing numbers of guiding variables when using sophisticated interpolation techniques. The use of automatic parameter selection techniques throughout this study allowed adaptive interpolations capable of capturing most daily temperature conditions with only 174 data points.

8.2.1.2 Interpolation of input temperatures versus the interpolation of model results

Practical investigation of the question 'should we be interpolating inputs or outputs?' in relation to insect phenologies has resulted in a generic set of considerations that could be asked as part of the modelling process. These relate to issues of computing environment, model complexity and further use of the results. Considering such a question set does not require a large investment on the part of the modeller, who may be reluctant to delve initially into multiple simulations to solve the problem without necessarily seeing any direct benefits. There may however be no clear answer, and a number of focused simulations are recommended in such cases. This study demonstrates the value of three metrics designed for this purpose:

- Comparison of root mean square accuracies between interpolation methodologies at known points;
- Checks for logical consistency between temporal outputs;
- Analysis of relative semi-variance in results between models run using actual input data,

interpolated input series and interpolated outputs.

Within an entomological setting, analysing the propagation of spatial and temporal errors in model predictions charts a new research area. Previous studies have interpolated results from phenological models unquestioningly, without incorporating checks on the spatial and temporal integrity of the process. The example of modelling the development of the Colorado beetle based on daily synoptic weather conditions shows that the common practice of interpolating the results of an at-a-point model will not *necessarily* produce results that are spatially and temporally coherent, even if point-based accuracy statistics (such as r.m.s.) seem satisfactory. In particular, logical inconsistencies in biological sequence may arise when interpolating phenologies that are avoided when interpolating inputs prior to running the phenological models. Problems associated with the interpolation of calendar dates also arise only when interpolating model outputs. The interpolation of model inputs is also particularly beneficial for modelling the later stages of insect development, where spatial association between phenological results may be highly localised in comparison to that of the daily temperature input data. The conclusion we can draw from this is that, while the interpolation of phenologies is often adequate, on a number of occasions this is not the case. In contrast, the more time consuming interpolation of temperature data as model input guaranteed the avoidance a number of problems, for example relating to logical error, which in some application areas may be highly critical.

More generally, the work highlights the need for further research to combine spatial and temporal error propagation methods and the need to understand the spatial significance of attribute error. We have shown that principles used to determine the integrity of spatial databases using logical rules may also be applied to spatio-temporal modelling procedures. The mathematical results for the particular phenological models exemplified are application specific. Nevertheless, the issues considered are generic to many other environmental models using time-varying inputs.

8.2.1.3 Error modelling

In this study, cross validation was used to provide daily sequences of *estimates* of maximum and minimum temperatures that were used to run the phenology models at the 174 known data points. These estimated inputs introduced the degree of inaccuracy arising from the remoteness of station data to the computation of phenologies. The model results computed on this basis could then be compared with model runs from known data at the same location. This approach to error propagation has not been found elsewhere within the recent GIS literature. It allows a direct assessment of the effect of remotely located input data on phenological predictions and the exploration of error propagation throughout the progress of the model through the insect lifestages.

Residual errors in the spatial phenologies computed using jack-knife cross-validation errors were explored using the accumulated temperature model running over three different base temperatures. It was found that spatial accuracies within the residuals from the accumulated temperature model were a compound construction of the errors discussed separately in Chapter 4 for maximum and minimum temperatures. The largest model errors were associated with locations in which the direction of bias in both maximum and minimum temperatures occurred in opposing directions. Differences in error distribution between accumulated temperature models run over different base temperatures highlighted the impact of seasonal variability in input errors at different locations. The adequacy of the modelling approach was confirmed by the absence of marked bias within the distributions of error from this simple model, which showed little bias (<5DD) and only minor skew.

The distribution of errors in the accumulated temperature model in the national extent, computed using actual independent temperature data received late in the project, were compared with those errors computed using the jack-knife cross-validation approach. The results from the two assessment procedures were found to be statistically similar over multiple configurations (base temperatures) of the model, once the dependence of the r.m.s. error on the different geometries/characteristics between the data sets was accounted for. The conclusion that can be drawn from this is that point-based cross-validation is a good surrogate for truly independent reserved data. This is an important finding, since many GIS and environmental modelling applications do not have the luxury of extra data to reserve only for testing purposes and it is not practical to field-validate many models.

Given the desirability of providing error surfaces to accompany the maps of insect phenology, the legitimacy was explored of the common practice of interpolating residual errors (DD) computed using jack-knife cross-validation using both inverse distance weighting and trend surface analysis. No spatial autocorrelation was measurable within the residuals. Comparisons between residuals computed using independent data and those of the interpolated 'error surfaces' showed that the r.m.s. error associated with the interpolated residuals was greater than that for the original model surfaces themselves. The conclusion to be drawn from this is that the interpolation of residuals from the interpolation process should be avoided. The derivation of error surfaces through the Monte-Carlo propagation of errors within each data layer, an alternative strategy, is unsuited to the national extent of the study that was required for PRA in the absence of a high-performance computer. Indeed, the exploration of spatial errors within individual data layers (in this case for example, daily maximum and minimum temperatures) using techniques such as conditional simulation has yet to be investigated thoroughly. A general conclusion from this evidence is that further theoretical and empirical research is warranted to combine spatial and temporal error propagation methods in an efficient manner. Heuvelink (1998) for example demonstrates the use of Taylor series when combining errors from several inputs, but such frameworks have yet to be developed for the propagation of multiple errors in space *and* time. Such explorations would be better suited to a local area study. Moreover, while the conditional simulation of daily temperatures or phenologies are interesting topics for further research in themselves, the resultant surfaces would remain only a *partial* estimate of the overall error in phenological prediction over the landscape unless error within the biological models could also be accounted for.

While complete error surfaces were not produced within this study, an improved understand the spatial significance of attribute error was nevertheless gained. Three metrics were devised in this study to show for the first time some of the geographical dimensions of logical errors. Principles used to determine the integrity of spatial databases using logical rules may also be applied to spatio-temporal modelling procedures. The mathematical results for the particular phenological models exemplified are application specific. Nevertheless, the issues considered are generic to many other environmental models using time-varying inputs.

8.2.1.4 Implementation issues

The successful modelling of parameters such as those of the variogram model for the majority of days in the year suggest that the meteorological data set used (174 points) was adequate for the study. However problems on a minority of dates (30%) suggest that an improved sample of data with more data at short lag distances in particular, together with an increased volume of data overall, might assist in improving overall accuracies given the national extent of the study. Given the spatial resolution of the study ($1km^2$) however, a degree of variation as a result of micro-climatic processes will always be expected and the accuracies achieved may be close to their limits.

The question 'Can the system be based upon a conventional GIS, or is an alternative structure required? was answered by the need to develop research software in order to perform the core interpolation and modelling tasks. The technology of geographical information handling was found to be considerably behind the science of the literature when seeking a sophisticated framework that would support the creation of operational systems for pest risk assessment. The four interpolation methods used for example, while in steady use for research over the past few years, are not found together within one proprietary software system. A lack of automatic parameter fitting techniques for interpolators, particularly important within applied studies with several input surfaces to be interpolated for each of many days, had to be overcome in this study, and would also be required for operational use.

Perhaps most importantly, the management of spatially-referenced sequences of temporal data is poor in all but bespoke systems. The system designed allowed an increased flexibility and efficiency in the way in which interpolation routines and biological models could be combined that allowed for example the computation and display of jack-knifed phenology results over time and the graphing of temporal phenology sequences at any location. These have not previously been seen in an insect-ecological context. While the pragmatic, loosely coupled approach adopted within the thesis was in keeping with the overall emphasis upon issues relating to geographical phenologies, much research remains to be done in the area of spatio-temporal data structures and the translation of conceptual approaches into dynamic modelling environments as outlined within Section 2.3.1. GISystems were used simply as an adjunct to the study, managing the data storage and permitting the visualisation of the geographical results.

From the perspective of software efficiency, making use of the dual associations between splines and kriging (Cressie 1991, Hutchinson and Gessler 1994) would further streamline the modelling suite. Additionally, the software developed as part of the thesis was aimed at supporting the exploration of a number of geographical research questions, rather than towards 'user friendliness'. The software framework is capable of being run by computer literature biologists, but the number of options and manipulations afforded means that it is presently unsuited for novice users desiring information and answers to specific recurring questions. An associated study developed a prototype windows interface using Arc-View™ to support the use of GEO-BUG for specific tasks relating to risk assessment (Gillick 1998), but this requires further refinement before it could be used operationally.

Since daily temperatures drive many biological and environmental processes, the design of a framework to couple models and inputs has considerable generic utility. By providing intermediate daily temperature surfaces rather than just final phenological results for example, the work could be used in conjunction with other sample and experimental data to explore hypotheses relating to insect overwintering. Additionally, modelling pest phenologies in this way was intended as a pre-cursor to the more complex task of understanding pest populations and their dispersal within space. The extension of the framework to other applications requiring temporal sequences of daily maximum and minimum temperatures was introduced though example risk maps for both pest populations (*Bemisia tabaci*).

8.2.2 Geographical insect phenologies

8.2.2.1 Indigenous pests: application to integrated pest management

Previous explorations of the value of interpolated temperature surfaces rather than data from the nearest meteorological station are unknown in insect ecology, although a small number of spatial phenologies (based on interpolated model results) have been explored in a North American forestry setting. This study is unusual in exploring geographical insect ecology for agricultural and horticultural applications. Applications of GIS within insect ecology are more commonly associated with empirical relationships between biological samples and landscape characteristics, rather than the modelling approach used here.

R.m.s. error in the date estimate across all 1st generation developmental stages for codling moth were found to halve when using temperatures derived from partial thin plate spline interpolations in comparison to nearest neighbour techniques. While much effort and investment is currently being applied to improving the underlying phenology models within complementary research projects, it is concluded that previous applied entomologies have focused on the biological modelling at the expense of considerations regarding input data. Even at the relatively crude 1km^2 resolution used, the use of locally relevant (interpolated) input data rather than 'nearest neighbour' meteorological information from the synoptic network has scope to improve the practical performance of well calibrated phenology models. While insect habitats are highly local, the field calibration to standard UKMO data of the phenology models used previously to this study means that the biological models themselves already compensate for an expected degree of local variation in prediction for terrain. While temperature surfaces at higher resolutions are desirable for more accurate biological modelling, therefore, in a pragmatic agricultural context the interpolated surfaces at $1km^2$ should be immediately applicable.

Partial thin plate splines were found optimal at 70% of point sample locations in England and Wales when compared with Voronoi estimates for estimating codling moth development. Additionally, the penalty for using splines (when sub-optimal) is small in comparison to estimates computed using the less accurate 'nearest neighbour' techniques. This confirms the need to use a more sophisticated approach to the interpolation of daily temperatures than in the limited previous studies (Russo *et al.* 1994). Nevertheless, nearest neighbour techniques on average grossly under-perform spline estimates in the majority of cases. The assumption among insect ecologists has been that interpolations are not necessary in flat agricultural areas. This has been shown to be not the case. From a decision analysis perspective, it is concluded that the results computed using partial thin plate spline interpolations provide an improved base for agricultural decision making. The assessment of error in insect phenology timing relating solely to remotely sited input data has not previously been assessed.

Consideration of the multiple phenological plots found throughout the thesis from the perspective of variation over space and through time suggests that variation in temperature over time is the dominant driver of codling moth phenology. Variation in space has a secondary influence but there are times when the spatial dimension is important, especially at the marginal areas for pest development. This confirms a need for the continued development of temporally sophisticated phenology models. Nevertheless, the work has shown that consideration of geographical phenologies can materially reduce the error in phenological estimates.

While additional independent testing of the phenology surfaces using biological samples could usefully be used to assess the overall 'fitness for purpose' of the geographical modelling results (as, in a limited way, has been reported in previous studies), field testing would provide a *combined* measure of error both as a result of remote input data and the biological model. In this work, the model error was assumed zero and the geographical enquiry focused on the error arising from sparse, poorly representative or limited numbers of meteorological stations for national daily temperature characterisation. The relative contribution of geographical and biological errors is a research area of considerable interest, but is one that would require additional trap and temperature recorder data together at unknown locations to enable analysis. Finally, the cross-validation approach provided a means of assessing the bounds of reliability in the phenological forecasts for non-indigenous pests introduced by the geographical approach for which, by their very nature, no independent biological sample data are available.

8.2.2.2 Non-indigenous pests: application to pest risk assessment

This thesis provides the first known use of phenology models for pest risk assessment, although hybrid techniques for estimating pest phenology or population based upon accumulated temperature are common within the literature. The national (England and Wales) extent of the geographical phenologies was critical for this purpose.

The use of daily input data allowed the production of results that, unlike the main body of work in pest risk assessment, express more fully the underlying variability and degrees of sensitivity of the pest with differences in climate. The incorporation of explicit phenology models, rather than an environmental index as used previously, allowed the date-based results to be tied in with the cropping cycle. Assessments were modified to take account of the main host crop, potatoes, using gridded digital crop data. From this it is concluded that risk statistics based upon the use of landscape wide phenology results without modification for land use may overestimate areas at risk considerably.

From the marked differences in pest risk from year-to-year indicated using fully spatial and point based methodologies, it is concluded that the potentially unrepresentative nature of point statistics for pest risk assessment causes assessments based on such data open to misinterpretation. Using point data causes the overestimation of pest development potential by greater than 30% of the land surface of England and Wales in a minority of years (1962, 1972, 1974 and 1986) when compared to figures generated using geographical phenologies. When assessing risk, a degree of cautious overestimation may be circumspect, the overestimation of development potential presented by the point based phenology results presents a discrepancy in the preferred direction. Nevertheless, it is concluded that these discrepancies raise alarms when considering the requirement for maximum objectivity in PRA as demanded by international treaty.

An aggregate risk index was introduced as a probabilistic representation of the likelihood that a pest might complete a single generation over the 'climate normal' period (1961-90) throughout the landscape on the basis of daily maximum and minimum temperatures. Previous work has ignored the assessment of year-on-year consistency in pest development in given locations as one means of analysing the likelihood of long-term establishment. The conclusions drawn from the findings of the study indicate that the possibility of underestimating a pest risk problem in extreme years: in twelve of the thirty years, the area estimated to be at risk is greater than the average. These results suggest that extreme but potentially significant events maybe under-represented when assessing establishment probabilities for a pest using long term climate average data. As in other risk assessment areas (e.g. insurance), this understatement may have considerable applied significance for British agriculture since inadequate controls (e.g. Quarantine status) may not be put into place. Fully spatial results, like point based results, are also subjective as a result of the ability to produce a range of maps according to interpolation approach and mathematical technique. Relatively, however, fully spatial results seem to provide a more objective means to produce an explicit geographical representation of risk for all locations.

The findings and structures put into place within the thesis go beyond those immediately reported, and differences of biological opinion on particular models (e.g. population vs. phenology, linear vs. sigmoidal) or thresholds could equally be incorporated for the building of consensus within a PRA. Threshold temperatures for development, flight or over-wintering capability have been exemplified, as has the more generic accumulated temperature approach. As Worner (1991) notes, simplicity where the underlying data and knowledge of a pest is sparse is preferable to an over-complex modelling stance. The focus upon temperature as the driving factor influencing pest development acknowledges this observation, while the ability to incorporate models of a variety of sophistication but with this restriction allows the PRA expert to incorporate the particular approach adopted according to its biological validity for a particular insect pest. Debates regarding the wisdom of phenological versus population models and the need to better account for insect over-wintering, together with caveats regarding the complexities of insect ecology, were highlighted within the discussions of Section 7.1. The modelling work contained within this thesis represents one particular biological stance in order to focus upon demonstrating the potential value of a geographical approach to assessing the risk of a pest becoming established within Britain following its initial arrival and spread. A comparison of different models and perspectives on pest risk assessment could be facilitated using the underlying structures developed within the thesis, and it is therefore concluded that the biological bias inherent in such a study does not deprive the geographical approach taken of any of its power.

8.3 Future related research possibilities

Suggestions for improving the work that relate directly to the methods used and data available for this study were incorporated within Section 8.2. In addition a number of further related research possibilities with less direct connection to the findings presented, but that link with the themes of insect ecology and GIScience of the thesis, may be identified. These include:

- *Multiple criteria approaches to sampling*

Consideration of the sampling/data selection issue as a multiple criteria problem was introduced within chapter 3. This allows a *combination* of factors such as the environmental characteristics and accuracy of the global data set, cost of data and further analysis techniques to be taken into account together when sampling or selecting data. While a number of traditional methods for multiple criteria analysis exist, an evolutionary approach to sampling is suggested chiefly for its ability to manage large data sets and compromise between factors. First steps towards this goal are reported as part of Appendix 13. While evolutionary approaches are commonly used within the Artificial Intelligence community to solve multiple criteria and objective problems, they have been little used in GIScience for these purposes to date.

- *Weather generation and forecast data*

The primary focus within this work was placed on the exploration of historical patterns of phenology using long-term climate records. However, a wider range of data will be required over different time frames to support real-time agricultural decision support systems. For day-to-day decision making (*operational* tasks), models require both pertinent historical data (e.g. weather to date in the growing season) and short range forecasts to be of assistance for pre-emptive management tasks. At a more *strategic* level, as an agricultural season progresses the use of a weather generating module in addition to the actual record to date would help to identify the potential future envelope of pest activity. Either weather generated or long term records might also be of assistance when considering alterations to planting schedules or crop varieties. The ability to perform 'what if' type explorations is characteristic of good decision support systems. While a limited number of examples of the use of non-spatial weather generators to identify long range fluctuations in pest activity may be found (e.g. Shirley, Port and Young (1999), the inclusion of spatio-temporal generators is less common (e.g. Semenov, 1998).

- *The derivation of additional, climate related, data inputs*

There is presently a significant gap between the amount of information presently available through the standard UK Meteorological Office network in 'real time', compared to the information required to support the production of interpolated data for agricultural decision making. This is particularly the case for rainfall and relative humidity, as preliminary explorations using the synoptic data set have shown. The results of this study relating to daily air temperatures suggest that users of decision support systems need these input data to be representative of the specific location where their model results are required, in both space and time domains. A system is therefore envisaged which collects, collates, validates and interpolates data from an expanded network of meteorological sensors. New technology for the automatic sensing of weather conditions could, through careful network merging procedures, allow more comprehensive and locally detailed meteorological data to be provided for input into interpolation procedures and subsequently agricultural decision support systems.

- *'Intelligent' interpolation*

The case for more supportive software toolkits and the need for 'expert' guidance is inter-disciplinary (e.g. Banerjee and Basu 1993). Burrough (1992) is among others (Densham and Goodchild, 1989, Cowen and Shirley 1991) within the GIScience community who expresses the creation of more 'intelligent' systems to support environmental decision-makers as a long-term research goal. Previous work using artificial intelligence techniques to assist specifically in the choice of interpolator have tended to use a simple rule based approach (e.g. Maslyn 1987, Dimitrakopoulos 1993) that is computationally efficient but highly domain specific (either in terms of application domain or interpolator type). This type of approach recognises the qualitative nature of much of the information and knowledge used when modelling. However, it does not assist the user in investigating whether the chosen technique will meet their accuracy requirements: an important element within integrated environmental modelling studies (Heuvelink *et al.* 1989). The development of an 'intelligent' interpolation module that would assist users through a variety of means is proposed. This might involve a two-pronged approach, with questions asked of the domain expert being supplemented for example by automatic error assessments, trend detection and parameter fitting.

- *Improved access to spatially relevant agro-meteorological data*

Linking with the need for a wider range of interpolated input data to drive agricultural models, in a British context, there is no one place where spatially referenced meteorological and soil data are consistently collated and updated at scales appropriate in both the temporal and spatial dimension for the current breed of agricultural decision support systems. Designers of decision support systems however need to hide the details surrounding the provision of such model input data from their users if DSS are to become an efficient tool within the workplace. This points to the use of a central service provider, processing and disseminating requests for model input data from users. The use of parallel GIS technologies may provide one means of ensuring adequate real-time response times. Developments in spatial data handling using the World Wide Web make an Internet service an unparalleled solution for a query and distribution function of interpolated data for modelling purposes. Research issues arise from management of server scheduling (Gittings *et al.* 1993), the design of an interface to assist users in extracting relevant spatio-temporal information (Carver *et al.* 1997) and the communication of uncertainty within the data to the users (Newton, Gittings and Stuart, 1997).

- *Insect population modelling*

The fragmented and non-continuous nature of populations relative to phenologies implies a different scale of investigation from that explored within this thesis. However, simple temperature-based population estimates are used in an applied entomological context, and have been incorporated within this research framework. The linking of crop models and information regarding crop-pest interaction with such pest models, as demonstrated by Kropff *et al.* (1995) would provide improved estimates of the economic impact of a pest. Firstly however, further biological experimentation would be required to parameterise the specific models used.

Knowledge of the inter-relationships between landscape structure and insect dispersal are an important component within the wider search for a better understanding of what constitutes ecologically and economically sustainable agriculture (Halley *et al.* 1996). Simulation models can be a valuable component in the iterative process of hypothesis generation and empirical fieldwork within environmental entomology, especially when considering invading species or possible extinction of populations. In both cases, a large number of controlling factors are interacting with the population and it is not tractable to study all of these elements using field studies alone. However, population modelling from local to landscape scales requires extensive consideration of a wide variety of factors. These include for example the provision of meteorological data (temperature *plus* other factors) at more local scales than considered within this study, consideration of predator/prey interaction and crop scheduling in addition to an improved understanding of the factors triggering dispersal. While GIScience, through the application for example of geographically referenced agent systems, provides structures for exploring these issues (e.g. Takeyama and Couclelis 1997, Wesseling 1996, Westervelt and Hopkins 1999), the depth of biological understanding and experimentation required means that the modelling of dynamic, rather than static, local insect populations will require considerable further inter-disciplinary study.

- *The modelling of crop diseases*

The scope of the thesis was limited to considering insect crop pests, rather than crop diseases. Most diseases are strongly dependent on climate factors such as relative humidity and rainfall. Exploring their geographical dimensions is therefore dependent on the interpolation of additional climate variables. In structure, many applied crop disease models are rule based rather than process based, making them potentially simpler candidates for exploring probability based risk surfaces through the use for example of Bayesian belief networks or indicator conditional simulation.

The thesis began with Kareiva's (1990) observation that, '*Simply saying that the spatial environment is important is to mouth a platitude: what we need to know is whether this presumed importance amounts to much in natural systems*'. In finishing, it can be concluded that within the specific application areas explored within the thesis, the use of phenological models in pest risk assessment and integrated pest management, the use of geographical rather than point-based phenologies had a demonstrable impact upon the results assessed. The research methods that have been outlined have allowed an investigation of a focused set of issues, and provide a platform for a number of avenues of future research both in GIScience and insect ecology.

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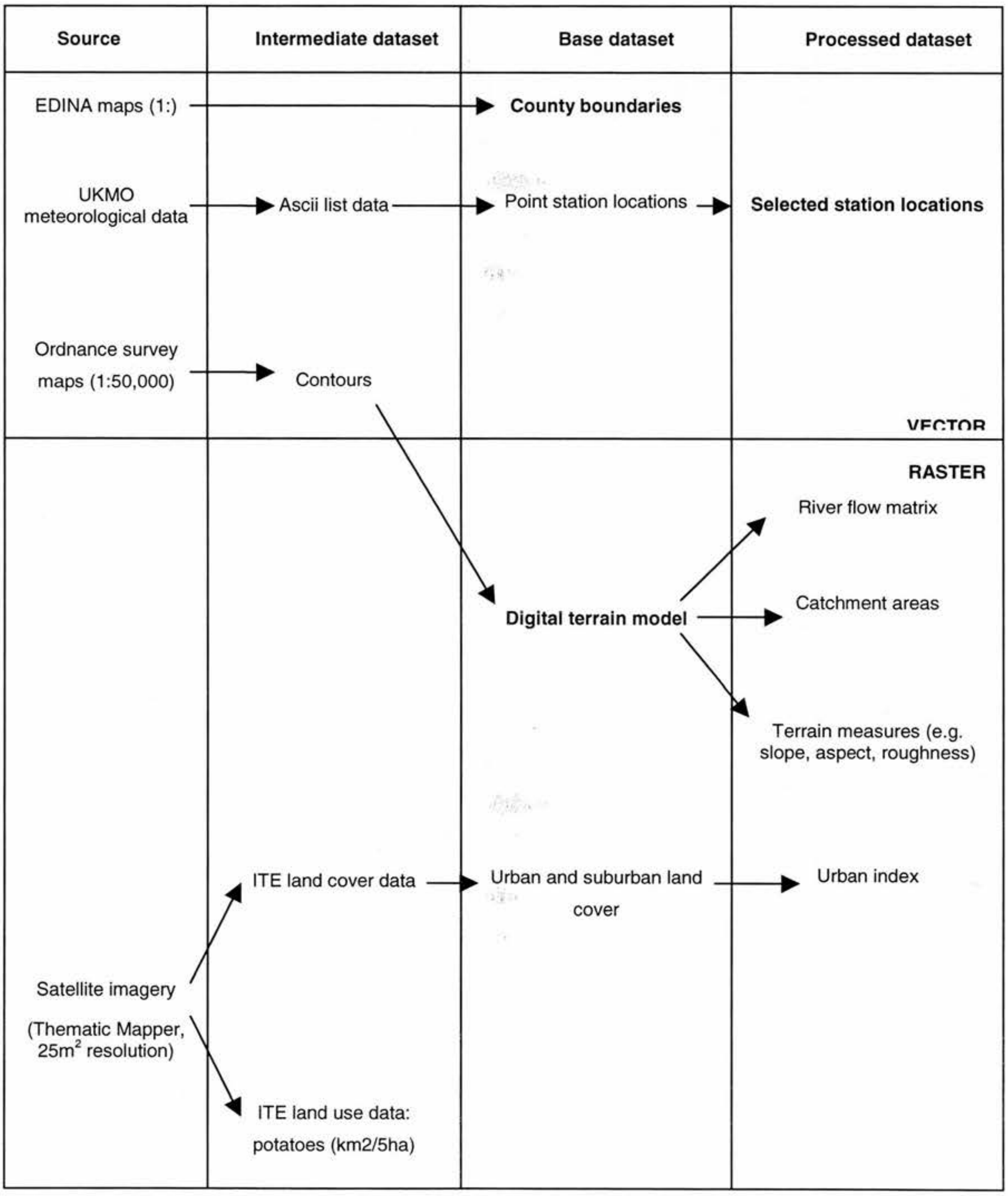
Appendix 1: Sources of data



Appendix 2: A summary of conventional search and optimisation techniques for solving multiple criteria problems

Conventional search and optimisation methods and their restrictions

Gradient analysis	• Search spaces are often calculus unfriendly i.e. non-differentiable and are difficult to define. • Local in scope (e.g. calculus (or gradient) methods) and may therefore converge prematurely at a non global solution • Not designed with multiple solutions in mind, which occur with competing objectives, and are therefore devalued as a decision support tool • Often highly tailored to solve a particular problem, so both may not be easily adapted and fail to enhance the GIS in other potential application areas • Not adaptable to situations with multiple solutions without many runs (Fonseca and Fleming, 1995)
Enumerative Mixed Integer Programming Dynamic Programming Overlay methods Hierarchical methods	• Solutions problematic to understand with increasing number of criteria (e.g. overlay analysis, Janssen and Rietveld 1990) • Loss of information using thresholds with continuous data and problems in defining thresholds in overlay analysis (Janssen and Rietveld op cit.) • Unable to compromise between conflicting criteria (e.g. hierarchical methods) • Not guaranteed to find a solution (e.g. Overlay/weighted linear combination methods or hierarchical ranking methods may render the entire search space 'unsuitable') • May not address combinatorial side of a problem (e.g. overlay/hierarchical methods ignore geographical relationship between possible sites, important in sampling context) • Unable to cope with large volumes of data (incl. dynamic programming, Schwefel 1995, p12) • Not necessarily adaptable to situations with multiple solutions in mind (e.g. simplex, Fonseca and Fleming 1995)
Random Random walks Random search and save	• Unable to cope with large volumes of data (choosing 200 sites from a total of 985 has 985!/((985-200)!*200!) possible combinations)

Appendix 3: A summary of Point Interpolation Method

METHOD	ADVANTAGES	DISADVANTAGES
Voronoi tessellation	• Simplicity of principle; • May be computed in multiple dimensions (e.g. Watson 1992); • Forms the basis for natural neighbour interpolation: smooth, area-weighted function with blended gradient information (e.g. Watson and Phillips 1987).	• Discontinuous surface; • No error estimates possible; • Strongly dependent on distribution of data.
Distance weighted (Assign more weight to nearer points than distant) Deterministic Local Gradual "Best for quick contour plots of moderately smooth data" (Burrough 1983)	• Exact(although for -ve exponential weighting, approximate only) Lam 1983) • Simplicity of principle (McCauley 1993); • Gradual transition (Burrough 1983); • Speed of calculation (Lam 1983); • Light to moderate computing load (Burrough 1993); • Ease of programming (Lam 1983); • Reasonable results for many data types (Lam 1983).	• Choice of weighting function ambiguous (Burrough 1983), although automatic fitting procedures may be used (e.g. Collins and Bolstad 1996); • Easily affected by uneven distribution of data points – more so than kriging; • Does not take into account the local geometric configuration of data points (Tabios and Salas 1985) – though quadrant segmentation implemented within SURFER (Declercq 1996); • How far apart before points deemed redundant is arbitrary (Burrough 1983, Lam 1983); • Simple versions assume isotropy and will obscure linear features (Burrough 1983, Watson and Philip 1985); • Smoothing effect-max/min beyond sample point range not possible (Burrough 1983); • Discontinuous surface (local extrema) at data points, although gradient versions have been developed (e.g. Tobler and Kennedy 1985, Watson and Philip 1985); • No error surface computable; • Not exact unless constrained (Burrough 1983); • Does not allow boundary specification (Pariente 1994).

Interpolating polynomial (Lowest order polynomial that passes through all data points, used in this study to refer to a trend/regression combination) Stochastic Global " Not generally recommended, particularly so when the number of data points is large" (Lam 1983)	• Simple, mathematically (Lam 1983); • Smoothing to identify predominant trend; • Can be done piece-wise - may be combined with Delauny triangulation constructs (Akima 1978, see below under TIN methods).	• Polynomial unconstrained, intermediate points may be wildly different from nearby points and unreasonable in value (Lam 1983); • Piecewise solution may have: (Lam 1983): • Discontinuities at edges; • High computation times. • Need to adjust for differing data densities; • Physical explanation for of trend may be unclear (Burrough and McDonnell 1998) • Global mean response trends may be confused with latent spatial autocorrelation (Griffith 1996); • Mathematical inaccuracies for polynomials of orders greater than 5 (Ralston 1965, in Lam 1983); • Assumes errors are uncorrelated; • Error assessment limited to overall goodness of fit; • High order polynomials give rise to visually improbable surfaces.
Ordinary kriging (Statistical surface as regionalised variable with degree of continuity) Stochastic Local (with global variograms) Gradual	• Fewer computational problems than universal kriging; • Most successful for phenomena with very strong random component (Mitás and Mitásová 1999); • Exact method; • Interdependence between sample points accounted for; • Provides kriging error variance and confidence interval; • 'Optimal' unbiased estimate since based on structure of sample by minimising known variance; • Anisotropy may be accounted for; • Robust relative to IDW to choice of parameters such as number of neighbours; • May be extended to include the temporal dimension (Bogaert 1996); • Assumes stationarity only within a neighbourhood (Lam 1983).	• Imply stationarity over space, but regionalised variables often non-stationary i.e. restrictive assumptions; • Heavy computing load (Burrough 1983); • Model fitting crucial to success, but is subjective (de-trending, model choice, parameter fitting method); • Requires appropriate data spacing; • Assumes data error have Gaussian form (Deutsch and Journel, 1992); • Assumes average local values continuous (Burrough 1983); • Computational intensive given size of accuracy payoff (Burrough 1983); • Selection of neighbourhood size difficult; • Requires large number of sample points (Webster and Oliver 1992); • Assumes average local values continuous unless stratification methods are deliberately used (Burrough 1983); • Less successful where local geometry important (e.g. terrain modelling, Hutchinson and Gallant 1999); • Kriging variance a poor measure of true error; • Drift/trend must be removed prior to modelling.

Indicator kriging As for ordinary kriging Provides estimates of the probability of a threshold being exceeded	• Provides probability estimate; • Binary or nominal data may be incorporated.	• As for ordinary kriging; • Invokes stronger stationarity assumptions than the other kriging estimators (Myers 1994).
Universal kriging As for ordinary kriging "Best for situations where the most detailed estimates and their errors are required" (Burrough 1983)	• As for ordinary kriging; • Assumes stationarity only within a neighbourhood (Lam 1983); • Allows direct incorporation of 'guiding variables'.	• As for ordinary kriging; • Computationally intensive (Burrough 1983).
Co-kriging As for ordinary kriging Enables the use of point auxiliary variables to improve kriging estimates	• Allows incorporation of a related variable for which there are more data when kriging an undersampled variable (Myers 1984); • Improves the coherence between estimated values by taking account of the relationship between the variables (Rivoirard 1994, p9).	• As for ordinary kriging; • Computationally intensive: variograms increase with the square of number of variables and co-regionalisation model needed for each (Rivoirard 1994, p10).
Disjunctive kriging Builds upon co-kriging, but using non-linear geostatistics. Sometimes referred to as indicator cokriging (e.g. Rivoirard 1994, p23)	• Relinquishes assumptions of linearity; • Allows estimation of the probability a threshold is exceeded (Rivoirard 1994).	• No easy source of software; • Relies on parametric models with restrictive assumptions (Deutsch and Journel 1998, p17); • Indicator kriging more flexible where cross covariances required; • Multivariate Gaussian model better understood and more robust for models with one covariance model (Deutsch and Journel 1998, p17).
Conditional simulation Local with global elements (variogram fitting, overall distribution) Stochastic	• Equally probable realisations may be produced (Journel 1996); • Patterns may be simulated (Deutsch and Journel 1998).	• Computationally intensive; • Avoid if smooth results desired.
Piecewise polynomial splines (Term 'spline' first used for cubic piecewise polynomial functions, Burrough and McDonnell 1998) (Bicubic splines in 3D) Local Deterministic Gradual	• Can be made an exact method (Lam 1983); • Piece-wise, so involve just a few local points at a time (Burrough 1983); • Analytic and flexible (Lam 1983); • Low order splines give sufficient accuracy (Lam 1983); • Accuracy high relative to distance weighting (Retain small scale features, Burrough 1983); • Aesthetically pleasing (Burrough 1983).	• Bicubic splines not simple cross products of univariate splines so complex; • Problem of defining patches, or neighbourhoods (Burrough 1983); • Anomalies introduced at patch edges (Burrough 1983); • Unsuited to irregular data (Declercq 1996); • Cause excessive undulations even for gradually changing surfaces (Declercq 1996).

B-splines (Search for least number of non-zero sub intervals – simplification of polynomial piecewise splines) Deterministic Local Gradual "Best for very smooth surfaces" (Burrough 1983)	• Visually appealing – designed for use in computer graphics; • Light/moderate computing load, (Burrough 1983) – locally tuneable tension (Mitás and Mitásová 1999.	• No estimates or error variance; • Often inaccurate (Mitás and Mitásová 1999); • Masks all uncertainties in surface i.e. over-smoothing.
Thin plate splines Global when using Hutchinson's (1991b) algorithm, (unless using selected 'knots', when local) Deterministic with local stochastic component Gradual	• Incorporates smoothing, so acknowledging measurement error; • Analytic and flexible (Lam 1983); • Require less data than geostatistical techniques; • Low order splines have proven accuracy (Hutchinson 1998); • Partial thin plate splines may incorporate linearly correlated guiding variables (Hutchinson 1991b); • Multi-dimensional (3d) splines feasible; • Unlike IDW or trend surface interpolation, small scale features retained (Burrough and McDonnell 1998 p120); • Automatic parameterisation using GCV (Hutchinson 1991b); • Known topographic features may be incorporated (Hutchinson 1989); • Computationally efficient; • Aesthetically pleasing results (Burrough 1983).	• Mathematically complex: difficult to implement unless software provided; • Problems with large data sets, when patches /neighbourhoods must be defined – although practical solutions now available (Hutchinson 1991b); • Potential anomalies introduced at patch edges (Burrough 1983); • Assumes isotropy, although a degree of local anisotropy possible between 'patches'; • Assumes errors are spatially uncorrelated (Diggle and Hutchinson 1989); • Standard software (Hutchinson 1991b) does not allow time as 3rd dimension; • Plate stiffness causes function to overshoot in regions where data create large gradients (Mitás and Mitásová 1999); • Potential for over-smoothing data (Burrough and McDonnell 1998, p120) • 2nd order derivatives diverge at data points, causing difficulties with surface geometry (Mitás and Mitásová 1999).
Regularised spline with tension Local (Global method applied in local patches) as computed by Mitásová and Mitás (e.g. 1993, 1996) Deterministic with local stochastic component Gradual	• As for thin plate splines; • Unlike thin plate splines, surface has regular derivatives of all orders; • May incorporate anisotropy through generalisation of tension parameter (Mitás and Mitásová 1997) and use of local patches; • Adapted to manage very large datasets and interpolation grids (e.g. Hargrove et al. 1995) • Multi-dimensional (3d/4d) splines demonstrated within a GIS environment (Mitásová et al. 1995).	• Greater mathematical complexity than thin plate splines; • Concern remains regarding the potential oversmoothing of natural phenomena (Miller 1994) • Local patches difficult to define when data are irregularly spaced (Hutchinson and Gallant 1999); • Potential anomalies introduced at patch edges (Burrough 1983); • Anisotropy limited to one direction across each surface patch (Hutchinson and Gallant 1999).
Neural networks	• Highly flexible; • Avoids mathematical/statistical assumptions, from normality/linearity;	• Hand coded, 'designer' solution;

Fourier Series Model (Surface decomposed into periodic surfaces with different wavelengths) Stochastic Global Gradual	• Most applicable if cyclical surface anticipated (Burrough 1983);	• Approximate (Burrough 1983); • Assumes strict periodicity in phenomenon of interest (Burrough 1983).
Triangular irregular network interpolation Deterministic Local	• Fast to compute (Mitas and Mitasova 1999); • Effective representation for dynamic visualisation and visibility analyses (de Floriani and Magillo, 1999); • Higher order interpolations ensure continuous first derivatives (e.g. Watson and Phillip 1984, Akima 1978); • Easy incorporation of discontinuities and structural features (Mitas and Mitasova 1999).	• Extension to d-dimensional problems more complex than for distance based methods (Nielson 1993); • Appropriate triangulation respecting the surface geometry is critical to success – sensitive to original data configuration (Hutchinson and Gallant 1999, Weibel and Heller 1991); • Among the least accurate of methods (Franke 1982, Nielson 1993).
Finite differencing (locally adaptive gridding) (Desired surface obeys differential equations which are approximated by finite differences and solved iteratively) Local Gradual	• Computationally efficient (Hutchinson and Gallant 1999); • Locally adaptive constraints allow the incorporation of anisotropy (Hutchinson and Gallant 1999); • Advanced developments for terrain modelling assist in maintenance of surface form (Hutchinson 1996); • Exact (Pariente 1994); • Accounts for boundary segments (Pariente 1994).	• Time consuming (Lam 1983); • Generated surface has no absolute or relative max/min except at sample points or boundary (Lam 1983); • Unnatural contouring may result (Lam 1983); • Potential overshoots in regions of rapidly changing gradients (Mitásová and Mitás 1993); • Interpolation beyond neighbourhood of data points is poor (Lam 1983).

Appendix 4: Similarities between kriging and thin plate splines

There are n data values $y(x_i)$ at positions x_i given by:

$$y(x_i) = z(x_i) + \varepsilon(x_i) \quad i = 1, ..., n$$

$z(x_i)$: Function to be estimated from observations $y(x_i)$

In SPLINES: assumed to be the values of a smooth unknown function

In KRIGING: values of an autocorrelated random field

ε (x_i): Discontinuous error term

Formally, thin plate splines and kriging may be connected by identifying splines as Bayesian estimates with respect to an appropriate prior multivariate normal distribution for the $z(x_i)$ of (1) above.

$z(x_i)$ may be estimated using:

In spline terms, (Hutchinson and Gessler , 1994):

$$f(\mathbf{x}) = \sum_{j=1}^{M} a_j \phi_j(\mathbf{x}) + \sum_{i=1}^{n} b_i \psi(r_i)$$

ϕ_j : A set of M low order monomials;

ψ : A scalar function of the Euclidean distance r_i between x and x_i;

m: Order of the derivative minimised to obtain f(x), on which M and ψ depend;

b_i: Restricted to satisfy boundary conditions;

ϕ estimated after the spline fitted using GCV; automatically specified by order of derivative *m*;

Usually requires order n_3 operations to solve a linear system of order n.

In kriging terms, after Matheron 1981 :

$$g(\mathbf{x}) = \sum_{j=1}^{M} a_j \phi_j(\mathbf{x}) + \sum_{i=1}^{n} b_i K(r_i)$$

ϕ : A set of low order monomials corresponding to the order k of the drift (Dubrule, 1984);

r_i: Euclidean distance between x_i and x ;

K: Generalised covariance function;

b_i: Conditions to ensure kriging estimator remains unbiased;

σ_ε^2 estimated first before surface can be calculated;

ϕ and k may be specified independently of covariance function K.

a_j and b_i: Formally equivalent between systems (Dubrule, 1984)

identical between systems if m=k+1

Similarities between kriging and splining systems (After Hutchinson and Gessler 1994, Cressie 1991 p180)

Appendix 5: Accumulated temperature model

UKMO algorithm for computing accumulated temperature using recorded daily maxima and minima (Anonymous, 1969)

```
Do t=1,n , ndays
    If (max_n <= base)                 DD = 0
    If (min_n >= base)                 DD = (max_n + min_n)/2 - base
    If (max_n-base) > (base - min_n)   DD = (max_n + min_n)/2 - (base - min_n)/4
    If (max_n - base) < (base - min_n) DD = (max_n - base)/4
    ACC_SUM = ACC_SUM + DD
continue
```

Example accumulated temperature information available from Internet databases

LOCATION OF STUDY: California	
DEVELOPMENTAL THRESHOLDS	
LOWER	10.0°C
UPPER	31.1°C
CUTOFF METHOD	not specified
METHOD OF CALCULATION	not specified
DEGREE-DAY ACCUMULATIONS REQUIRED FOR EACH STAGE OF DEVELOPMENT	
HOST: Apple and pear	DD (°C)
EGGS	87.8
LARVAE	261.7
PUPAE	239.4
GENERATION TIME (EGG TO ADULT)	588.9
PRE-EGGLAYING ADULTS	32.2
GENERATION TIME (EGG TO EGG):	621.1
SET OUT TRAPS	Bud break
BIOFIX	When traps catch moths on two successive nights AND when sunset temperatures are above 16.7C.
PRE-EGGLAYING ADULTS	32.2
EGGS	87.8
AVERAGE EGG HATCH	120.0

Example 1. Codling Moth, In *Integrated Pest Management for Apples and Pears*. University of California Statewide Integrated Pest Management Project. Div. Agr. Sci. Publ. #3340.

LOCATION OF STUDY: California	
DEVELOPMENTAL THRESHOLDS	
LOWER	10.0°C
UPPER	31.1°C
METHOD OF CALCULATION	Not specified
CUTOFF METHOD	Horizontal cutoff
DEGREE-DAY ACCUMULATIONS REQUIRED FOR EACH STAGE OF DEVELOPMENT	
HOST: Walnut, Apples, and Pears	DD (°C)
FIRST GENERATION	588
SECOND GENERATION	657
THIRD GENERATION	657
MEAN GENERATION TIME	619

Example 2. After Pitcairn, Zalom, and Rice (1992).

(After University of California Statewide Integrated Pest Management Project Phenology Model Database, © 1996 The Regents of the University of California) (http://www.ipm.ucdavis.edu/PHENOLOGY/codlingm.html

Appendix 6: PETE parameter file

PETE parameter table for Colorado beetle (After Baker and Cohen, 1985)

```
Enter values at RH side of spaces provided, beside punctuation marks
******
Title= COLORADO BEETLE
******
Select type of Development Function to be used
It must be the same for all stages except DIAPAUSE
Enter  DD  for Degree-days,  NL  for non-linear.
Then Temperature Sum in column 1 or Parameters for non-linear equation as F5.1
Also enter habitat of stage and temperature used (correction to be implemented
later)
******
```

Particular pest (generic file structure)

Threshold temperatures for development to begin, by stage

```
Function  DD;
Eggs   110.0  0.0  0.0  0.0  0.0    LEAF   Y  AIR
Larvae 230.0  0.0  0.0  0.0  0.0    LEAF   Y  AIR
Pupae  205.0  0.0  0.0  0.0  0.0    SOIL   N  AIR
Preov   50.0  0.0  0.0  0.0  0.0    AIR    N  AIR    Soil in winter
Adult  500.0  0.0  0.0  0.0  0.0    AIR    N  AIR
IK(Eggs)  =  20; IK(Larva)=  15; IK(Pupae)=  15; IK(Preov)=  10; IK(Adult)=  5;
DELTA   = 1.5;
******
```

Initialise with young adults at varying percentages of emergence

```
Starting values(IR). NB: SPACING IS CRITICAL. **** REMEMBER IK LIMITS ****
Egg   0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Larv  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Pupa  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
P-ov  5  70  20 5  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
Adlt  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
******
```

Base temperatures, by stage

```
Oviposition distribution (IOVIP)
IOV   20 50 20 10 0 0  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
******
Enter Base and Top temperatures for degree-day calculation (Baskerville and Emin)
BASE(EGG) = 7.0; BASE(LAR)= 10.5; BASE(PUP)= 9.5; BASE(P-O)= 8.5; BASE(AD) = 8.5;
******
Enter Completion threshold temperature for moult to the next stage.
COMPTH(E) =10.0; COMPTH(L)=10.0; COMPTH(P)=11.0; CMPTH(PO)=10.0; CMPTH(AD)=10.0;
******
Enter Activity Parameters
ACTEMP   = 15.0; ACTIME  =806.0; AV    = 10.0; ACTSUN  = 5.0; ACTWET  = 2.0;
******
```

Activity indices

Additional thresholds for development e.g. of photoperiod

```
Enter parameters for Diapause Induction
O/W Stage=  4; DD for Oblig Diapause   =5000;
Daylength at start of diapause induction=15.00;
Daylength at 100% diapause =13.00;
Julian day at start of diapause=194;
******
Enter parameters for Diapause Development;
Diapause stage(Enter 0 if diapause function not required) 00;
Parameters for Prediapause(DD)(2F7.1)   0.0   0.0
Parameters for Quadratic (5F12.8) 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000
```

Appendix 7: Topoclimatic variables

Variable	Description
Easting	Easting per national grid
Northing	Northing per national grid
Elevation	Height per OS 50m digital elevation model coarsened to 1km
Seadist	Distance to sea (all directions)
Eastdist	Distance to east coast
Westdist	Distance to west coast
Southdist	Distance to south coast
East100	Distance to east coast, influence limited to 100km
West100	Distance to west coast, influence limited to 100km
South100	Distance to south coast, influence limited to 100km
Pcoast4	Percentage of land cover within 4km grid
Pcoast25	Percentage of land cover within 25km grid
Urban	Urban index – function of size of settlement and %urbanisation
Rdist	Distance to nearest 'river' of any size calculated using OS 50m DTM
Rdist1	Distance to nearest 'river' of Strahler order 1
Rdist2	Distance to nearest 'river' of Strahler order 2
Rdist3	Distance to nearest 'river' of Strahler order 3
Rough25	Height minus 25km^2 grid mean
Rough5	Height minus 5km^2 grid mean
Stdev25	Standard deviation of local 25km^2 grid: local roughness
Stdev5	Standard deviation of local 5km^2 grid: local roughness
Drop10	Cell height minus 10km^2 grid minimum
Drop4	Cell height minus 4km^2 grid minimum
Htlarge	Height above large catchment (av. 1600km^2 wide) minimum
Htmedlar	Height above medium catchment (av. ??km^2 wide) minimum
Htmed	Height above medium catchment (av. 400km^2 wide) minimum
Htsmall	Height above local catchment (av. 9km^2 wide) minimum
Htbasin	Height above base of local basin
Aspect	Function of aspect (north = -1, south = 1)
Concave	Measure of concavity (-ve) /convexity (+ve)
Down	Degree of curvature down slope over 3km
Cross	Degree of curvature across slope over 3km
Highwest	Maximum altitude to the west
Hightwest	Maximum altitude to the west in 25km to north and south sweep
Highsouth	Maximum altitude to the south
Hightsouth	Maximum altitude to the south in 25km to east and west sweep

Appendix 8: Intrinsic hypotheses of kriging

Two fundamental assumptions (*intrinsic hypotheses*) are critical to kriging:

1. As Webster and Oliver (1990) note, the first assumption has taken various forms in different schools of research. In Matheron's original form, the expected value of the variable, E, is:

   $$E[Z(\mathbf{x}) - Z(\mathbf{x}+\mathbf{h})] = \phi$$

   for all points x and all vectors h, where ϕ is the linear drift.

   $$E[z(\mathbf{x})] = \mu$$

   Subsequent work by Journel and Huijbregts (1978) has used the narrower assumption:

   That is, the expected value of the variable is constant is said to be 'stationary in the mean' (Webster and Oliver 1990).

2. The second is that

   $$E[(Z(\mathbf{x}) - Z(\mathbf{x}+\mathbf{h}))^2] = 2\gamma(\mathbf{h})$$

   (a stationary variogram), $\gamma(h)$ exists and depends only on h (i.e. not on the position vector $\mathbf{x}$). In this case, is the semi-variance, defined as half the expected squared difference between sample values $\mathbf{Z}$ separated by a given distance h. The variance of the differences will be stationary for any lag.

A pragmatic result of kriging's intrinsic hypotheses is that all global trends should be eliminated within a data set before attempting to krige. Stationarity of the variogram is not a necessary theoretical requirement of kriging, although is often quoted as such. However, the assumption is critical in as far as it allows the variogram to be estimated from the data $\mathbf{Z}$. Making the assumption those properties can be regarded as stationary within small neighbourhoods, say of size v, is known as *quasi-stationarity* in $z(\mathbf{x})$-$z(\mathbf{x}+\mathbf{h})$. This leads to the following model of variation:

$$z(\mathbf{x}) = \mu_v + \varepsilon(\mathbf{x})$$

where $z(\mathbf{x})$ is the value of the property Z at $\mathbf{x}$ within the region, μ_v is the mean value within the region and $\varepsilon(\mathbf{x})$ is a spatially random component with a mean of zero and a variance defined by

$$\text{var}[\varepsilon(\mathbf{x}) - \varepsilon(\mathbf{x}+\mathbf{h})] = E[\{\varepsilon(\mathbf{x}) - \varepsilon(\mathbf{x}+\mathbf{h})\}^2] = 2\gamma(\mathbf{h})$$

The sample variogram is an estimate of this theoretical function calculated from a finite number of points:

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{[z(i) - z(i+h)\}^2$$

where $N(h)$ is the number of pairs of the observations separated by distance h. Given the irregularity of distribution between meteorological sites, it is likely that the sample semi-variogram will be estimated relatively poorly at small distances where the number of possible data pairs is small. As the distance increases, the number of data pairs for the calculation of the semi-variogram initially increases.

Ordinary kriging, implemented within this study, also requires the predictor to be uniformly unbiased; this is achieved by ensuring that the coefficients of the linear predictor sum to 1:

$$Z(x) = \sum_{i=1}^{n} \lambda_i Z(x_i) \qquad \sum_{i=1}^{n} \lambda_i = 1$$

(Where Z is the random function, $Z(x_i)$, $i=1,\ldots,n$ are the data measurements, x the estimation point and λ_i are the weights which minimise the error variance).

On the basis of the definition of the semi-variogram function, it is possible to minimise the error variance and solve equation 1. Following this minimisation, the weights of the equation are computed as follows:

$$\sum_{i=1}^{n} \lambda_i \gamma(x_i - x_j) + \mu = \gamma(x_j - x), j = 1,\ldots,n$$

$$\sum_{i=1}^{n} \lambda_i = 1$$

where μ is a Lagrange parameter and the minimal estimation variance in the point x, called the kriging variance, is:

$$\sigma^2(x) = \mu + \sum_{i=1}^{n} \lambda_i \gamma(x_i - x)$$

Kriging is 'optimal' in the sense that mean square predictor error is minimised in this context.

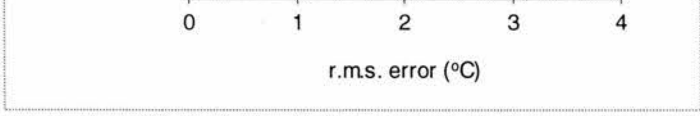
Appendix 9: Sundry temperature results

Comparative interpolation accuracies (ARC-INFO™)

Preliminary explorations were undertaken to investigate the accuracy of interpolation algorithms within proprietary GIS for interpolating maximum and minimum temperatures.

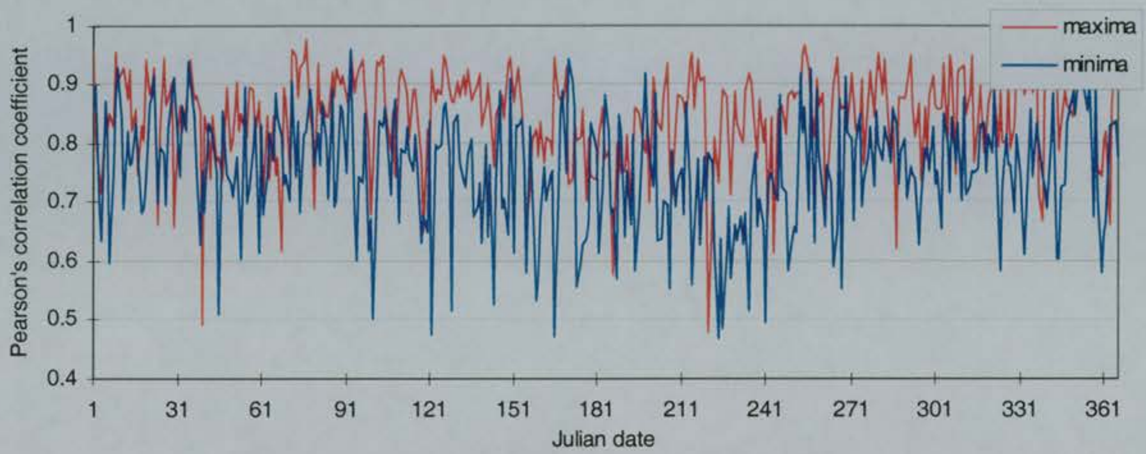
- The initial data set of 58 sample points was used;
- Results were computed for 10 randomly selected days in the year;
- The following techniques from ARC-INFO were used:
  - 2nd degree trend surface;
  - Inverse distance weighting;
  - Smoothing splines (S. Spline);
  - Tension splines (T Spline).
- Partial thin plate spline interpolation (Hutchinson 1991, P Spline)

The figure below reports the 'best' results from each set of experiments. Multiple iterations of smoothing and tension parameters, and IDW power parameters, were made to arrive at the results plotted. While the smoothness seminorm used in Hutchinson (1991) and ARC-INFO is not exactly the same, the value of automatic fitting procedures used within the thesis can be argued from these findings. The results for IDW in comparison with partial thin plate splines also demonstrate that the differences between the accuracies of the interpolation techniques are small, and are dependent on both the volume and location of data together with their daily variability.

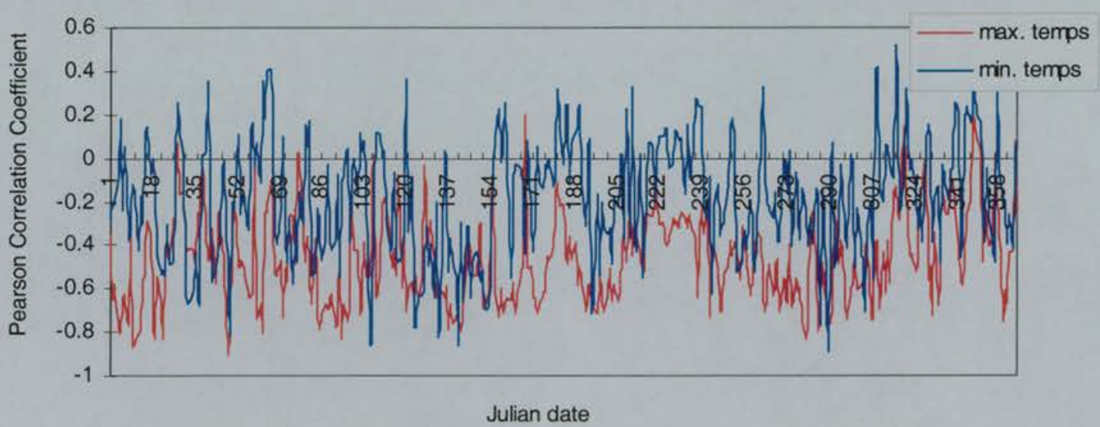


Accuracy of interpolation techniques for estimating maximum and minimum daily temperatures using ARC-INFO functions

Sundry correlation results

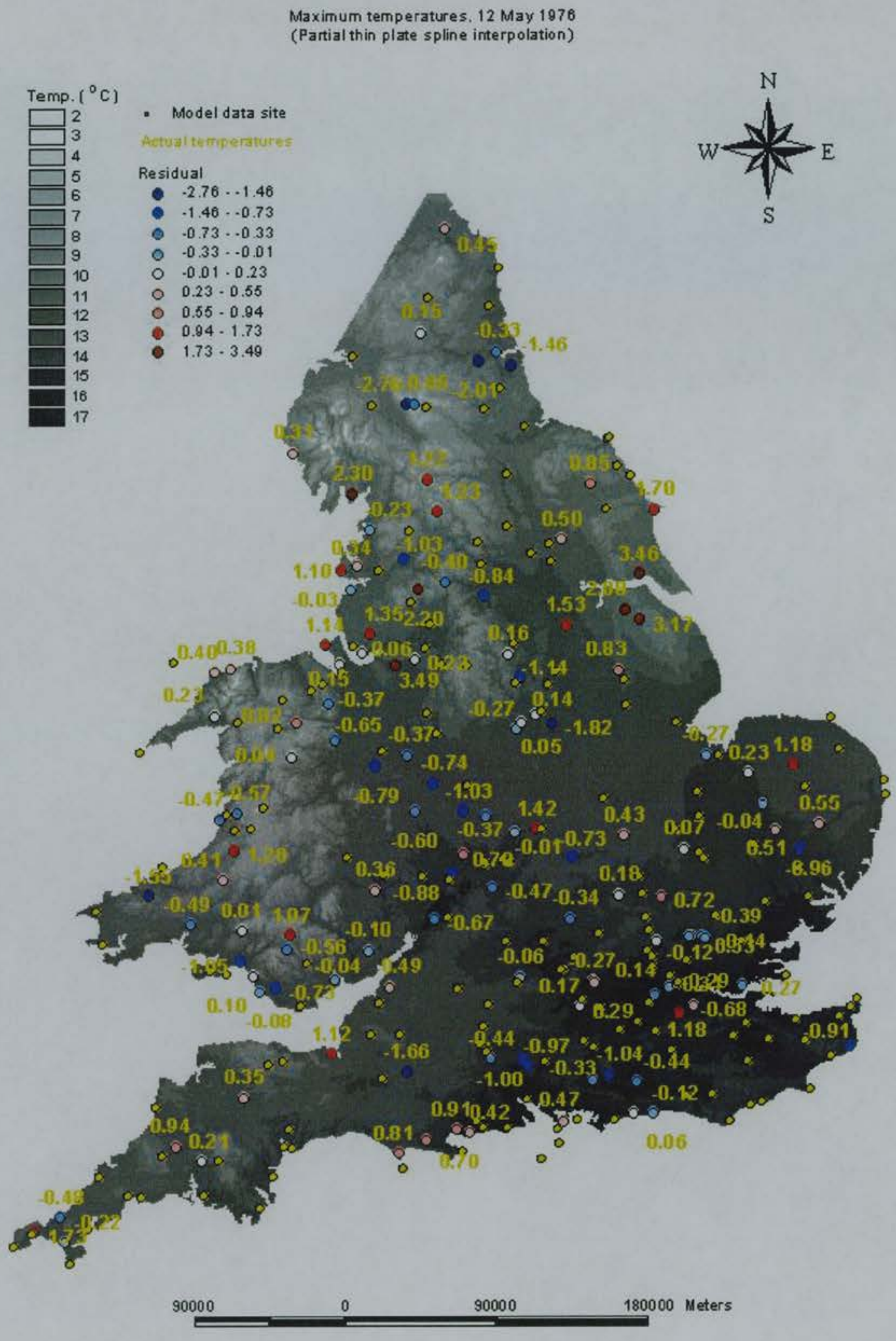


Pearson correlation coefficient between estimated and actual daily temperatures, partial thin plate spline interpolation, 1976

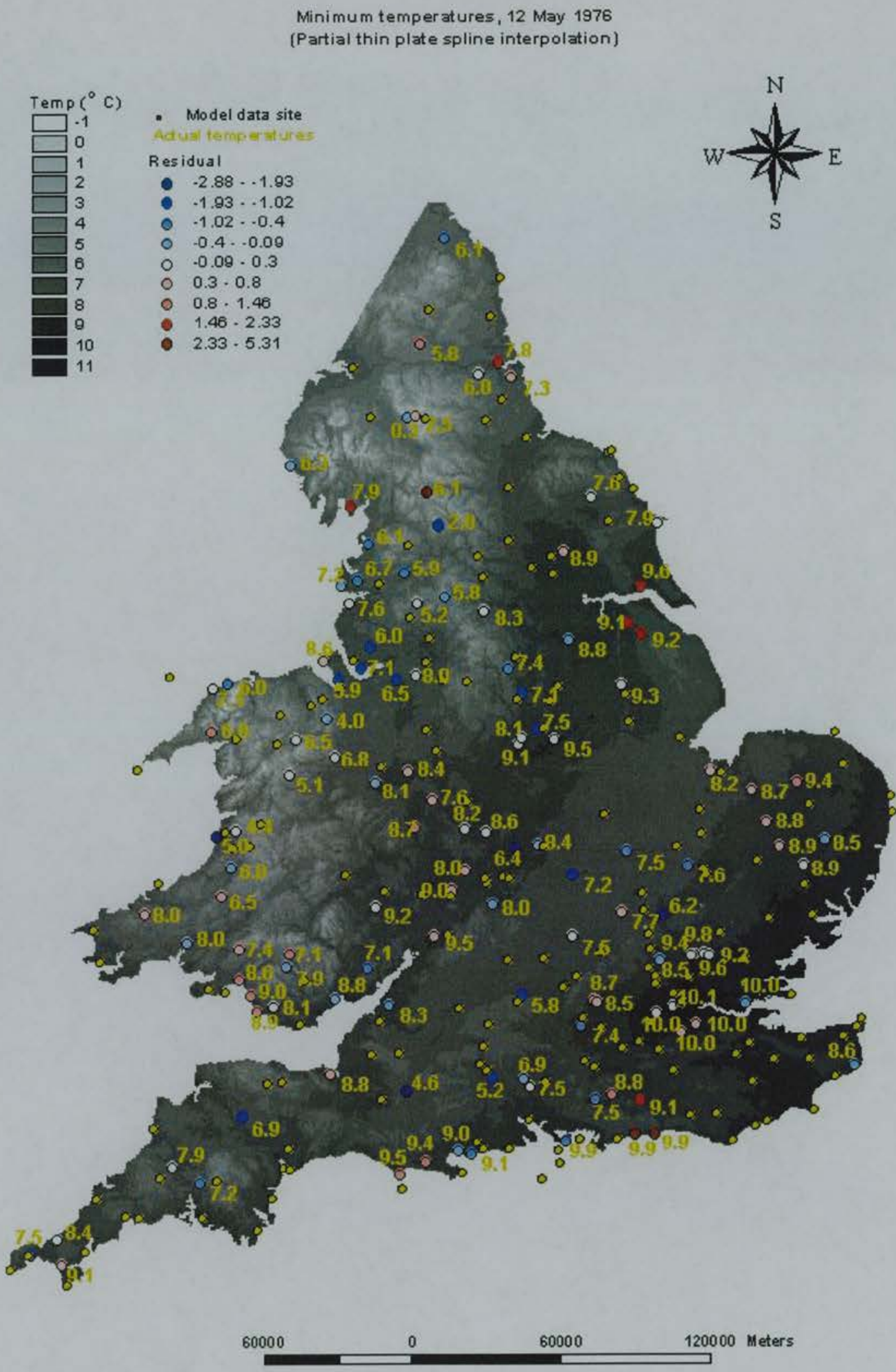


Correlation between daily maximum and minimum temperatures with height, 1976

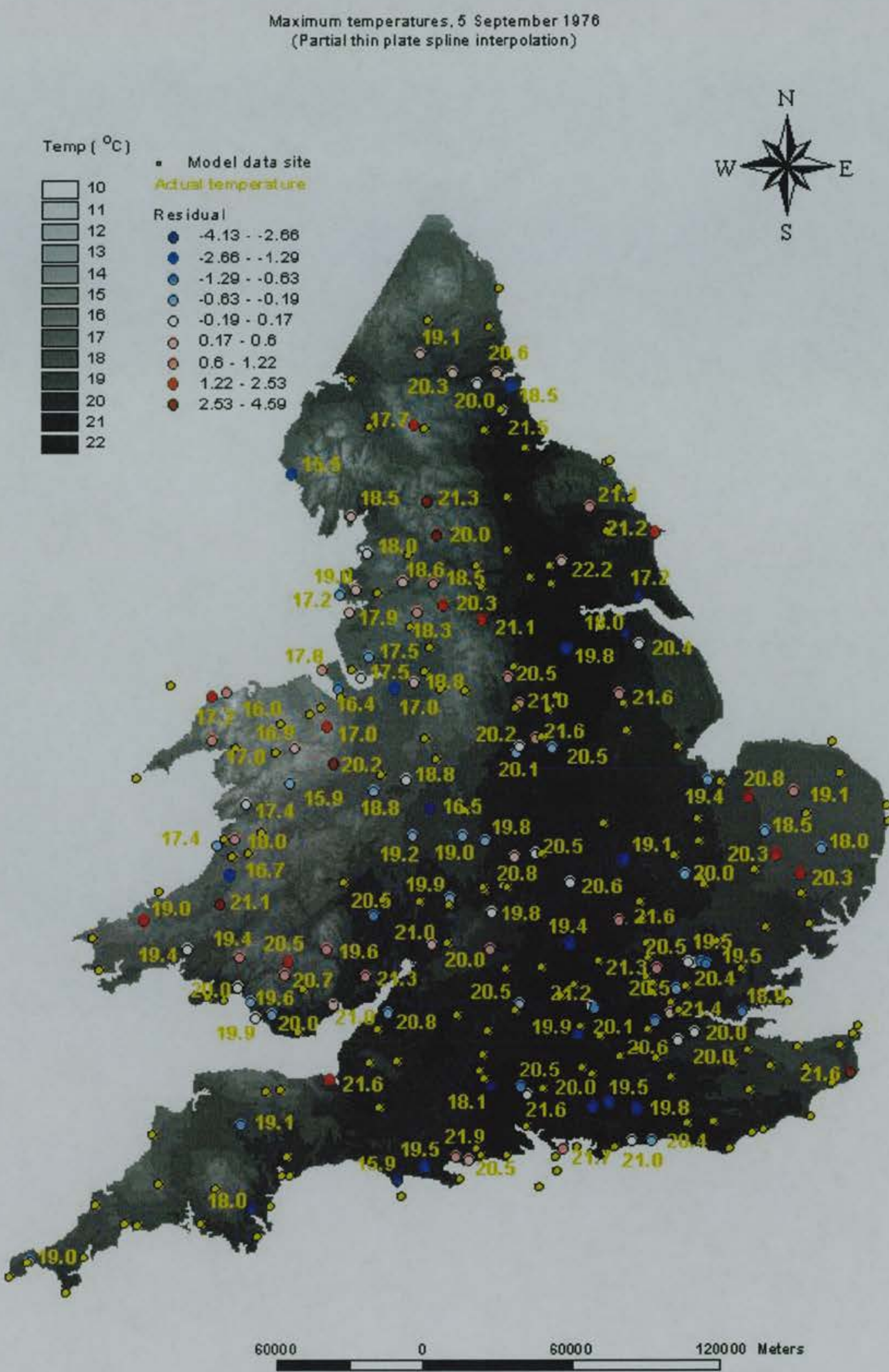
Appendix 10: Temperature plots



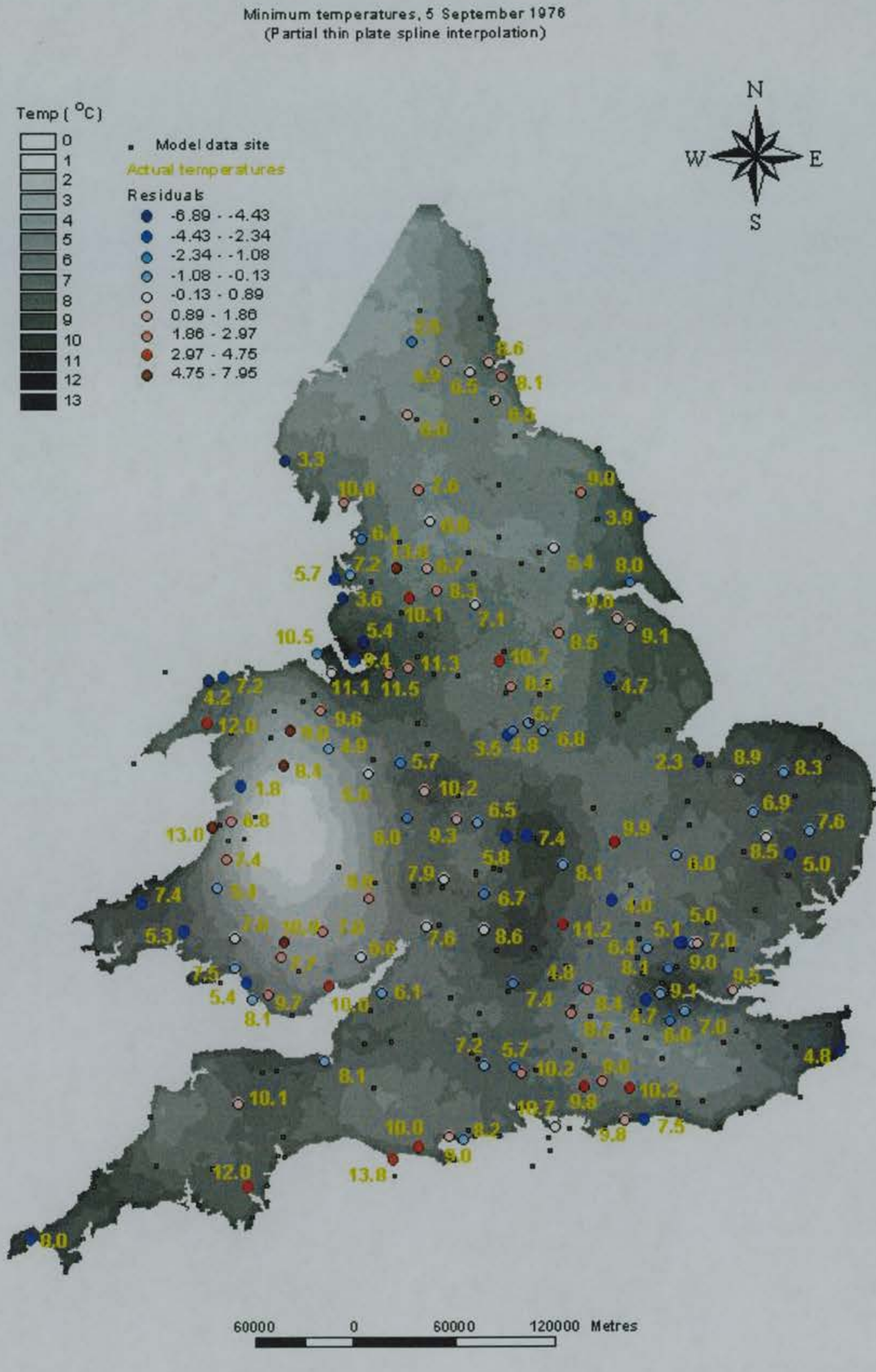
Maximum temperatures and residuals, 12 May 1976, by partial thin plate spline interpolation. Actual temperatures at withheld points (yellow, °C) with residuals (actual -estimated temperature) computed using additional independent data



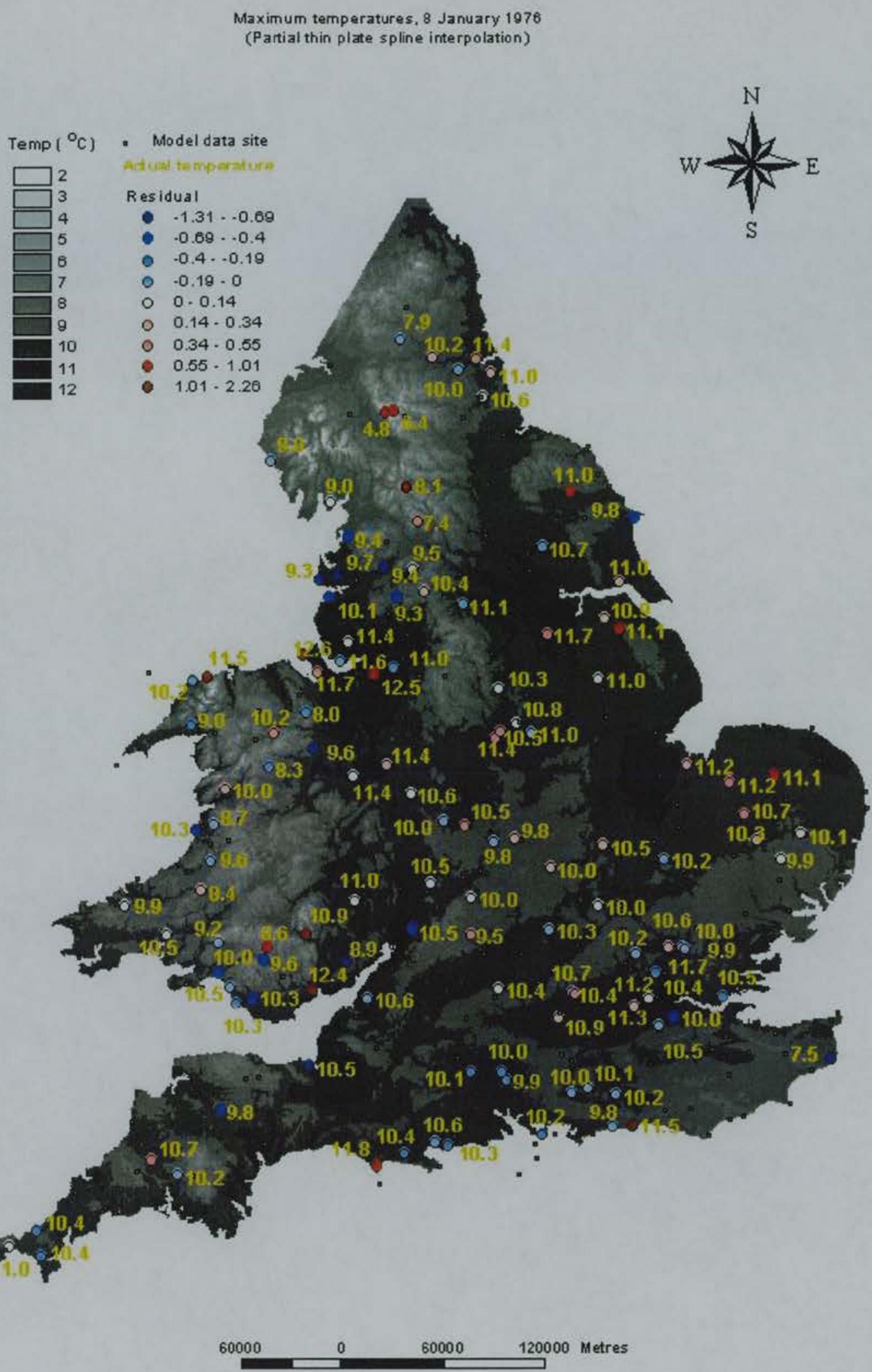
Minimum temperatures and residuals, 12 May 1976, by partial thin plate spline interpolation. Actual temperatures at withheld points (yellow, °C) with residuals (actual -estimated temperature) computed using additional independent data.



Maximum temperatures and residuals, 5 September 1976, by partial thin plate spline interpolation. Actual temperatures at withheld points (yellow, °C) with residuals (actual -estimated temperature) computed using additional independent data

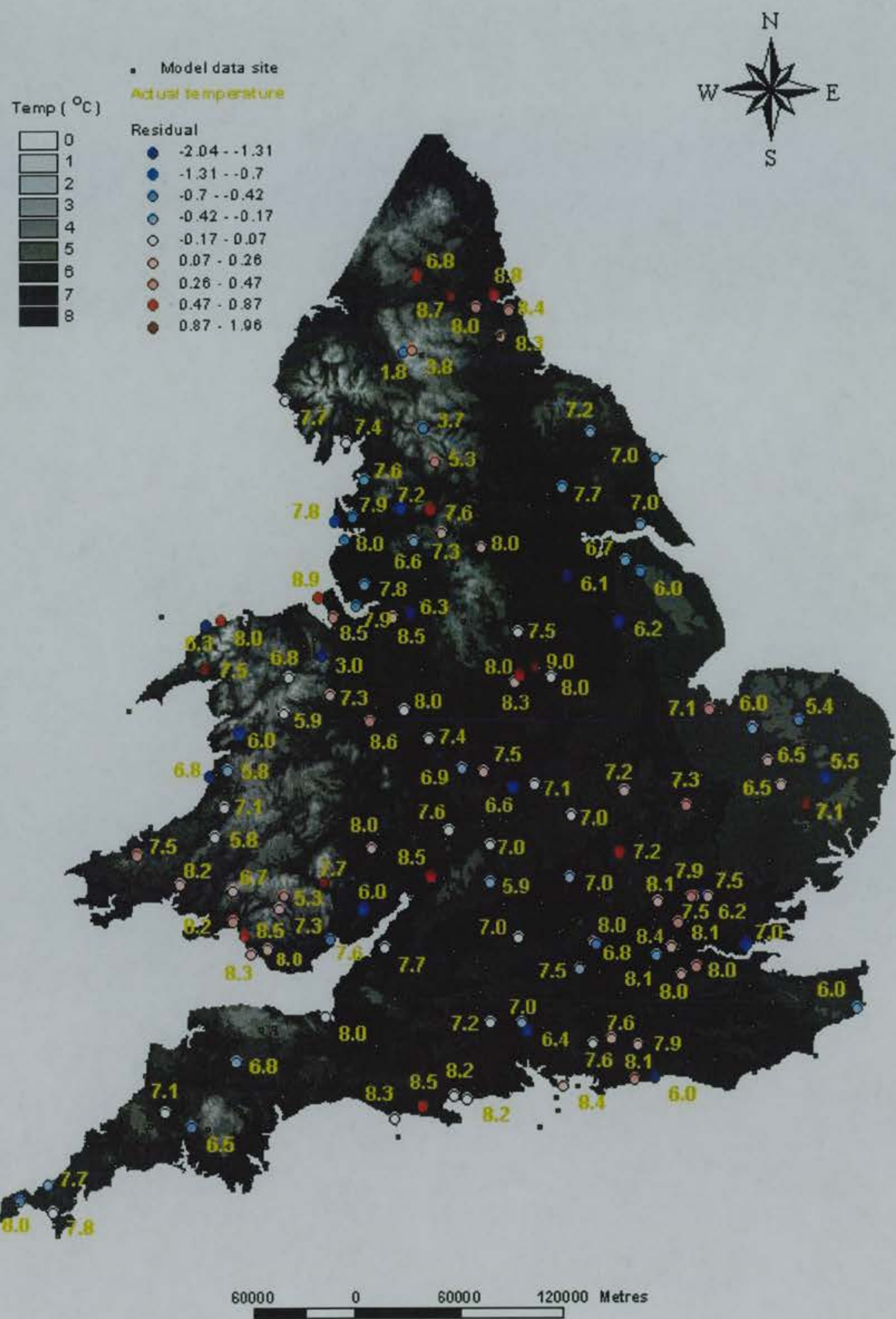


Minimum temperatures and residuals, 5 September 1976, by partial thin plate spline interpolation. Actual temperatures at withheld points (yellow, °C) with residuals (actual -estimated temperature) computed using additional independent data



Maximum temperatures and residuals, 8 January 1976, by partial thin plate spline interpolation. Actual temperatures at withheld points (yellow, °C) with residuals (actual -estimated temperature) computed using additional independent data

Minimum temperatures, 8 January 1976
(Partial thin plate spline interpolation)



Minimum temperatures and residuals, 8 January 1976, by partial thin plate spline interpolation. Actual temperatures at withheld points (yellow, °C) with residuals (actual -estimated temperature) computed using additional independent data

Appendix 11: Program files and subroutines

File name	Subroutines
acctemps.f	bio_model, getaccsum, bio_params
actuals.f	actual_bugs
charles_loop.f	main_charles_loop
climate-sensitivity.f	climate_change, alter_climate
csl_calgrd.f	rdsurf, calsur, dcalttwo
gam2v.f	gamv2
gcv.f	gcv_calculations, calpnt, npnts_gcvcalc
grid_tc.f	setfilenos,getlim,getsur,getcovs,int_technique,getvar,getind,calgrd,tidy_files, open_outfiles, headers
idw_interp.f	idw
julian_acc.f	bio_model, bio_params, getaccsum
krig.f	krig_param, krig_grid, readparm, krig_set, okb2d, krig_pnt, ksol
linset.f	dpofa, dposl, dqrdc, dqrsl, dsvdc, daxpy, dcopy, drotg, dswap
local_stats.f	getisg
main_gcv.f	main
main_grid.f	main
main_point.f	main
mintemps.f	bio_model, bio_params,mortality_data
my_splin0.f	setup, check, const, dcalt, dcalk, wrcof, resid, dqrsla, dqrslb,dqrsl2, dtrslb, dtrmlb.,opt1,opt2, minfun, wrstat, vsrtr
parse_met. f	parse_data, startend, met_search, getfdt, closing_up, siteinfo, jul
parse_met.f	start_end, julian
point_tc. f	setfilenos, int_technique, getcovs, getsur, getlim, getvar, open_outfiles
regress.f	regress, trend_grid, dtrend, trend_pnt, retrend_grid, retrend_initial_points, retrend_point,
reports. f	report_sites, sites_pnt, get_sites
sensitivity. f	climate_sensitivity, alter_climate
sub_bemtom. f	bio_model, disnorm,alocat, daylth, hourtmp, dev,devup, surv,repro, wegg, bio_params
sub_derek. f	bio_model, cod_graph, cod_output, bio_params, ratlog, devsur, daylnth, header
sub_lifemet.f	bio_model, bio_params, delays, degday, diadev, indip, activ, getpar, writpr, gstart, output, graph1
sub_splina.f	splina, getfil, getdat, rdata, ppara, opara, tridag, trisol, coeffa, calfta, diaga
var_fit.f	opt_param, param_est, mrqcof, covsrt, gaussj, vmodel, fpow, fgauss

Appendix 12: Meteorological data requirements for agricultural decision support systems

Summary of meteorological data requirements for agricultural decision support systems (Essential elements in capital letters)

Daily values	Crop growth/yield	Pests	Diseases
Max and min temp.	YES	YES	YES
Rainfall	YES	Yes	YES
Wind speed		Yes	Yes
Wind run			Yes
Total radiation	YES	Yes	
Relative humidity	Yes		YES
Soil temperature	Yes	Yes	
Evapotranspiration	YES	YES	
Ground frost frequency	YES		

Appendix 13: Published papers

Towards a Methodology for Selecting a "Characteristic" Sample from an Existing Database: An Evolutionary Approach

Jarvis, C.H.*, Stuart, N.*, Kelsey, J., Baker, R.H.A.

Paper presented at the 3rd International Conference on Integrating GIS and Environmental Modelling, January 21-25 1996 (CDROM: NCGIA, Santa Barbara).

Towards a Methodology for Selecting a "Characteristic" Sample from an Existing Database: An Evolutionary Approach

Jarvis, C.H.*, Stuart, N.*, Kelsey, J., Baker, R.H.A.

ABSTRACT

The performance of an environmental model depends highly on the 'representativeness' of the sample data with which it has been developed in relation to the overall data set, together with the adequacy of the sample with regard to the modelling technique itself. While advances have been made towards achieving both goals individually, in few cases are these combined. Additionally, the situation with regard to pre-existing data at fixed points remains 'ad hoc'. Given that increasing volumes of pre-sampled point data now exist in electronic form, these omissions are an issue of currency within the wide range of topics embraced by the term 'environmental modelling'. That this increase in data richness has frequently been matched by the rising cost of data means the ability to select appropriate data is paramount not only in terms model quality but also in the economic feasibility of the overall project itself. A new sampling methodology is presented to deal with these issues, framed within the context of the choice of meteorological station data for the development of interpolated weather surfaces but of wider applicability.

Fundamental to the new strategy is the representation of sampling requirements by means of a multi-criteria function. Criteria are developed to deal with each individual variable, for example a desired height function/range or the maximisation of record length. Data selection may also be tailored to the model types for which the data is to be used, for example by ensuring that an adequate number of nearby points are selected for interpolation by kriging. This combination of possibly contradictory criteria are then optimised together using a genetic algorithm in conjunction with the geographical information system in which the data are stored. While the solution of multi-criteria problems can be achieved using a variety of more traditional techniques, the GA approach was chosen both for its ability to manage large volumes of data and for its management of compromise. As a working progress report, discussion focuses on the reasons for the choice of an evolutionary approach and the representation of the sampling problem within this framework.

INTRODUCTION

However sophisticated a model or procedure, the results will only be as good as the data/knowledge underpinning its conception. This statement in itself is not new or radical and a number of sampling methodologies are very familiar in a wide range of disciplines. Such techniques include for example the random, stratified or systematic families of sampling. More recently these familiar methods have been augmented by those such as gradsect sampling (Austin & Heyligers, 1989) which deliberately sample across steep gradients of environmental change. Such moves highlight an increased awareness of the need to maximise the possible environmental range within a sample. Additionally, work by biologists Margules & Stein (1989) stressing the limitation of sampling within one dimension only has been applied within a geographical framework (Lees 1994, Aspinall & Lees 1994). The latter argue that not only should sampling be carried out with respect to full range of environmental criteria, but that each environmental space should be sampled individually. Further dimensions to the sampling problem that are difficult to incorporate within the context of traditional sampling methodologies include the purpose for which the data is to be used (e.g. Pettitt & McBratney, 1993), together with strategies which formally take into account the cost of sampling within the overall sampling objective (e.g. Bras and Rodriguez-Iturbe, 1976). What may be summarised from the current literature therefore are the concepts of representative data, the need to look at multidimensionality and the possibility of tailoring our sample according to future analytical requirements.

In the case of choosing the most characteristic pre-located site data from a wider set, as distinct from a free choice of sample sites over a particular landscape, the means by which all of the principles discussed above may be applied within the sampling process is somewhat ad hoc. Such a situation is however frequently to be found with the increasing volumes of pre-sampled data available in electronic form, the task of choosing relevant data becoming commensurably awesome. Even when a restricted and relevant data exists, its full cost may deem a project economically not viable and therefore a means of partial selection critical. Applying the definition of Eastman (1995) which classifies problems with a single objective (making an 'appropriate' sample choice) subject to a number of possibly conflicting criteria (representative data, multidimensionality, analytical requirements, cost) as multi-criteria evaluations, techniques for solving such problems within the broader literature are used as a base for further methodological discussion. It should be noted that some ambiguity in the use of such terminology arises even within a GIS environment, Jankowski (1995) referring to both multi-criteria and multi-objective techniques as 'multiple criteria decision making methods'.

A wide variety of traditional optimisation and search techniques exist which have been drawn upon in the development of 'multiple criteria decision making methods' (Table 1). As Schwefel (op cit, p165) notes, 'the question of which is the best strategy is itself a kind of optimisation problem' ! Just as multi-objective analysis has tended to be viewed as a 'natural extension of mathematical programming' (Jankowski 1995), so have the overlay and hierarchical methods of multi-criteria analysis found favour within the context of a geographical information systems (e.g. Carver 1991, Eastman et al 1995).

Gradient analysis	**Enumerative**	**Random**
	Mixed Integer Programming	Random walks
	Dynamic Programming	Random search & save
	Overlay methods	
	Hierarchical methods	

Table 1, CONVENTIONAL SEARCH AND OPTIMISATION METHODS

(After Goldberg, 1989, p3)

While a straightforward solution to the multi-criteria sampling problem was sought, a number of disadvantages in using these conventional methods were identified. These are summarised in Table 2 below.

Gradient analysis:

Search spaces are often calculus unfriendly i.e. non-differentiable and are difficult to define.

Local in scope (e.g. calculus (or gradient) methods) and may therefore converge prematurely at a non global solution

Not designed with multiple solutions in mind, which occur with competing objectives, and are therefore devalued as a decision support tool

Often highly tailored to solve a particular problem, so both may not be easily adapted and fail to enhance the GIS in other potential application areas

Not adaptable to situations with multiple solutions without many runs (Fonseca & Fleming, 1995)

Enumerative methods:

Solutions problematic to understand with increasing number of criteria (e.g. overlay analysis, Janssen & Rietveld 1990)

Loss of information using thresholds with continuous data & problems in defining thresholds in overlay analysis (Janssen & Rietveld op cit.)

Unable to compromise between conflicting criteria (e.g. hierarchical methods)

Not guaranteed to find a solution (e.g. Overlay/weighted linear combination methods or hierarchical ranking methods may render the entire search space 'unsuitable')

May not address combinatorial side of a problem (e.g. overlay/hierarchical methods ignore geographical relationship between possible sites, important in sampling context)

Unable to cope with large volumes of data (incl. dynamic programming, Schwefel 1995 p12)

Not necessarily adaptable to situations with multiple solutions in mind (e.g. simplex, Fonseca & Fleming 1995)

Random search:

Unable to cope with large volumes of data (choosing 200 sites from a total of 985 has 985!/((985-200)!*200!) possible combinations)

Table 2, **RESTRICTIONS OF CONVENTIONAL ALGORITHMS**

In addition to conventional search and optimisation algorithms, a newer class of methods known as evolutionary algorithms (incl. genetic algorithms) has also been used in multi-criteria optimisation (Goldberg, op cit, p197). Because of the major obstacles emerging should traditional methods be used in the case of the sampling problem (search space size, the objective as a collective of suitable sites, and conflicting criteria selection) these more recent techniques are evaluated for their potential use in the sampling application. The results of this analysis are shown in Table 3, from which the decision to develop a genetic algorithm approach to the extraction of a characteristic sub-sample of fixed data points from an established database was taken.

Work from a large number of points simultaneously, so climbing many 'local' peaks in parallel and therefore improving upon simulated annealing in addition to traditional hill climbing methods (Michalewicz, 1992, p29)

No auxiliary information in the form of derivatives is required, although the prior tabulation of distances between sites is needed for efficiency

Makes use of guided but randomised search to give wider coverage of data space than that provided by deterministic methods (Schwefel op cit p109)

Use of 'codings' of parameter set, rather than parameters themselves, means that GAs are largely unconstrained by previously mentioned limitations such as continuity, derivative existence etc. (Goldberg, op cit, p7)

General, rather than specific, technique allows code and methodology to be used for a wide variety of tasks when coupled with a GIS subject to alteration of coding/objective functions (travelling salesman e.g. Goldberg op cit, p170; groundwater pollution containment, Ritzel et al 1994; facilities siting, Pereira et al 1993)

But, theoretical study of multi-criterion evolutionary algorithms is lacking (Michalewicz, op cit, p9)

Table 3, ADVANTAGES OF EVOLUTIONARY COMPUTING APPROACH

METHODOLOGY

In developing a new sampling methodology, the first question to be asked is 'what is required of the sample data?'. As established within the literature review, the two main goals should be the 'representativeness' of the data with regard to the overall problem space, and the tailoring of data to suit the requirements of further analytical techniques. Specific criteria relevant to the search may then be introduced within the framework of more general evolutionary code. The local context of the sampling problem therefore requires close analysis. In this case the use of the sample is in the interpolation of point type meteorological data for England & Wales. The problem task is to choose a total of 200 sites from a possible 985, the number of sites restricted for economic reasons. The available meta-data for each site, derived data and its source are detailed below (Table 4) and in the first instance exclude partial or subjective data such as quality statements.

Meteorological office	**GIS** (Ordnance Survey 1:50,000 raster height data)
Location	Height
Start of recording (year)	Second derivative of slope
Record length	Aspect
Age of information	
Currency of data	

Table 4, SOURCES OF META DATA REGARDING EACH SITE

Derivations have been developed within the GIS GRASS or by spreadsheet, and move the initial data closer to a form useful in meeting the sampling criteria which are outlined below

A. Goal 1: 'Representativeness' of sample data relative to full data set

Adequate coverage of sites throughout country

Distribution of aspects representative of those of UK as a whole

Distribution of heights representative of total range within UK

B. Goal 2: Sampling requirements related to interpolation tasks

Nearby sites required for successful production of variogram

Long records required for improved temporal predictions

Currency of data important for management of future infestations

Where data recording has stopped but site important for other characteristics, time since recording discontinued

Table 5, DEVELOPMENT OF SAMPLING CRITERIA

Straightforward formulation of the criteria into 'fitness' functions does not however necessarily imply ease of optimisation, as hinted at by the ease in which more traditional approaches may be discounted in this problem case. A number of methods o f multi-criterion optimisation using evolutionary techniques exist, and this subject in itself forms an area of active research. Indeed, Fonseca & Fleming (1995) suggest that for the related multi-optimisation problem that it is time that an experimental approach be taken to real-world problems. Choice of method incorporates the two main issues involved within the evolutionary approach, those of fitness assignment (or suitability of the site) and search strategies (the probabilistic search through discrete space). In the main, attention has been given to the former (e.g. Jankowski 1995) and thus this is where the main alternatives lie. Given the apparent lack of comparative material and a desire to maintain simplicity where possible, the most straightforward of approaches is chosen firstly: the use of the popular aggregation (weighted sum) approach to fitness familiar from other techniques together with standard (Michalewicz, 1992) search operations.

The basic implementation of the evolutionary approach is summarised below (After Davis, 1991):

- Initialise a population of chromosomes (Where each chromosome is composed of 200 randomly selected sites (genes), selected from the possible 985 sites)

  e.g. site1, site3, site16, site89, site59, site895 ... gene 2 = site 3, gene 5 = site 59

  A floating point rather than the more conventional binary representation is used to prevent prohibitively long strings. This also has other advantages: it is intuitively closer to the problem space, facilitates the design of problem specific operators, and is faster and more consistent (Michalewicz, op cit, Chap. 5). This means that the approach used is not strictly that of a 'pure' (Goldberg 1989) genetic algorithm, hence the use of the broader term evolutionary algorithm..

- Evaluate each chromosome in the population according to its fitness (Fitness assignment) (Where fitness equals the weighted sum of each of the seven (normalised) individual criteria fitnesses, akin to approaches developed for use with conventional optimisers)

eg. Height fitness for chromosome 1 within the population (population = 200)

f(height)= (max. height - min height)/max. range possible within all 985 sites

Create new chromosomes by mating current chromosomes, using procedures of crossover and mutation (Search strategy) and where the probability of breeding relates to fitness.

eg. simple, single point crossover (crossover point = I)

Initial two strings: s1, s4, s6 I s768, s500, s345 ... , s98, s687 I s27, s879, s56 ...

Result: s98, s687, s768, s500, s345 ... s1, s4, s6 s27, s879, s56 ...

eg. mutation.

A value selected for mutation is replaced by a randomly generated number between that variable's lower and upper bounds

In both cases, the possibility exists to create illegal combinations, that is strings in which a particular site appears more than once. For the promotion of diversity, no repair algorithm was applied to the crossover operation on the basis that the fitness function rewards a spread of points. The basic algorithm was however altered to prevent any illegal mutations from occurring, and additionally f(nearness) was amended to avoid rewarding duplicate sites.

A further issue arises when the contribution of one gene to fitness depends on the value of another gene (Epistasis). This can lure the evolutionary algorithm into sub-optimal convergence, as explained by Michalewicz (op cit, p52). Because this situation arises in the case of the height fitness for example, an inversion operator was incorporated within the methodology that aims to group the maximum and minimum height genes together within a string to form an important building block.

e.g. inversion

Initial string: s1, s4, s78, s627, s3, s783, s876 ... , max. height = s4, min height = s783

After inversion: s1, s4, s783, s78, s627, s3, s876 ..

- Delete members of the population to make room for new chromosomes
- Evaluate new chromosomes and insert them into the population
- If the set number of generations is up, terminate and return the best chromosome
- Repeat experiment five times and average results

RESULTS AND DISCUSSION

In order for the evolutionary approach to sampling to be evaluated, its advantages and improvements compared to older strategies must be displayed. A major problem facing the study in this regard is that the performance of the evolutionary algorithm is a vector. Because of conflicting criteria, such as the requirements for sites to be spread throughout England and Wales together with the reward of nearby sites in order to be able produce an adequate variogram, a number of non dominated solutions are likely to exist owing to compromise. How therefore can a set of runs be evaluated? Perhaps only by the relative performance of the sample data in producing an interpolated data surface. However, because this experiment is set within the context of a real requirement for meteorological data, only meta-data is as yet available.

Instead, average initial results of the overall fitness of the solution were compared to that from a simple deterministic methodology in which sites were 'weeded' in a sequential fashion according to each criterion in turn, ranked according to perceived importance. While using this comparative technique selections could be made relatively straightforwardly according to second derivative of slope, age and continuance however, problems arose in incorporating the full range of environmental parameters such as height and in balancing a good spread of sites with adequate nearest neighbours in geographically varied areas. The overall fitness value achieved by the ad hoc technique compared well with the 'best' value of the initial random populations of the evolutionary algorithm but unsurprisingly was not well balanced within the scores for individual criteria.

One of the obstacles to the wider application of evolutionary algorithms is the need to experiment using a number of parameters such as the mutation rate, the probability of crossover between populations, population size used and the form of the operators themselves. The success of the evolutionary procedure may be shown by reference to the average convergence curve of fitness per generation over several runs using identical parameters from different random start points and additionally the use of different strategies from similar start points. Work in progress currently shows a steady increase in the average fitness of the total population per generation, with slower gains in 'best' fitness. This steady increase in average population value indicates a performance better than purely random and that the methodology holds promise. Nevertheless, it is the case that further tuning of the crossover and mutation rates is required, and alternative evolutionary operators such as expected crossover and mutation and ranked crossover are currently being explored. Also, the weighted sum method which aggregates all individual fitnesses within one overall, compensatory function is acknowledged as being sub-optimal in comparison to more sophisticated algorithms such as Shaffer's (1985, in Michalawicz 1992) VEGA system which rank populations according to pareto dominance (the ranked position according to each individual criterion, not accumulated fitness). The current formulation does not allow for the generation of two sets of sites for both testing and training, but this could be achieved in future work by the use of a double objective function.

CONCLUSIONS AND FURTHER DIRECTIONS

While simplistic in evolutionary computing terms, in comparison with traditional sampling methodologies the technique outlined appears rather complex. However, the approach outlined does allow for the sampling of 'fixed point' sites of data both characteristic of the underlying landscape spaces and tailored for analysis. To date, only ad hoc alternatives exist. Additionally, with the tailoring of the criteria and therefore the fitness function, the methodology developed is equally applicable to the selection of other geographically referenced point data, such as for example soil survey results and indeed to very different geographical problems.

In order to facilitate the exploration of a wider variety of genetic operators and parameters, work is undergoing to visualise the problem search space according to the defined function as a means of guidance. The generation of equally representative training and testing site combinations in order to avoid over reliance on cross-validation techniques is also underway.

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To interpolate and thence to model, or vice versa?

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To interpolate and thence to model, or vice versa?

Claire H. Jarvis, Neil Stuart, Richard H. A. Baker, Derek Morgan

18.1 INTRODUCTION

Most environmental models take as their input a sequence of parameters that are observed at only a limited number of points. There are many practical circumstances in which one wishes to extend these models to make spatially continuous predictions. In such cases, the question arises whether to interpolate the inputs to, or outputs from a model into an output grid (Figure 18.1). The issue is important because the two approaches differ in the efficiency and quality of the results that are produced. With the number of situations in which dynamic environmental models are being linked to GIS now expanding rapidly, this is a generic and as yet under researched question that the GIS and environmental modelling communities need to tackle.

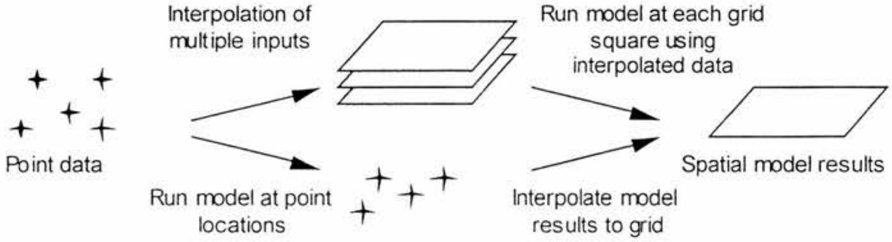

Figure 18.1 Interpolation of inputs to, or outputs from a model (After Burrough, 1992)

The question whether to interpolate or to model first arises on any occasion when a user needs to provide point data input to a model that is evaluated at multiple locations. In cell based GIS, the solution is usually first to interpolate the scattered points to a fill the grid layers, then to run model computations on the multiple input grids (e.g. Aspinall and Pearson, 1996). In more recent work a further temporal element has been introduced to this question by the linking of time-dependent point process or rule based models within a spatial setting (Burrough *et al.*, 1993). When incorporating time series of input point sets, the number of intermediate grids to be created by the 'interpolate first' method is multiplied further by the number of days.

Many ecosystem models are driven by climatic variables that are highly dynamic over time (Cramer and Fischer, 1996) but for which data is sparsely distributed over space. If we wish to run an ecosystem model over space, do we really need to estimate how values of each input variable change in relation to the changing environment away from meteorological stations? Alternatively, might the ecosystem be equally well represented by running the model at locations only where the condition has been directly observed and then interpolating the results? This shows how the question arises practically in many applications where dynamic modelling requires spatial data inputs, including fire management, hydrological, crop yield, pest risk and nutrient transfer models (e.g. Kessell, 1996; Landau 1996).

The question posed has rarely been considered explicitly within the published literature. Burrough (1992), viewing the issue in terms of error propagation, suggested that the question could be solved using fully spatial multiple simulations. For applied scientists already frustrated by practical difficulties in the management of data and computational performance of current proprietary GIS when modelling in space-time (e.g. Johnston *et al.*, 1996), this may be considered impractical. Work by Heuvelink (1998) and Arbia *et al.* (1998) among others have progressed our ability to model error propagation within environmental models in space, but the temporal element in such processes has still to be addressed. For both practical and intellectual reasons therefore, in applied studies often a decision to interpolate model outputs rather than inputs has been made. The application area for this case study, that of pest risk analysis, exemplifies this situation (e.g. Régnière *et al.*, 1996).

This work explores the interpolation-modelling issue for three models of varying complexity in the domain of insect ecology. Inevitably the structure of mathematical simulations within any case study are highly context dependent. Empirical studies are needed to allow us to quantify the magnitude of error that may be introduced into a single model result by choosing the less computationally intensive method of interpolating the point based outputs of a model. With many models working on sequences of daily or hourly data inputs, it is vital to know if errors introduced at each time step could also affect the logical coherence of these results if they are mapped out over time (temporal coherence) at a given place. The application area of insect ecology provides a realistic and thorough situation for testing, because rates of pest development may vary considerably over the landscape in both space and time. Models of insect ecology are complex in their treatment of processes acting over time in compared to many time-independent and rule based environmental models that have often been coupled with GIS.

Our analysis concentrates on quantitative errors within the attributes, rather than in position, as these are usually considered the more important component of error in environmental data analysis (e.g. Heuvelink, 1998). Focused numerical analysis is coupled with practical observations in order to provoke modellers into considering the broader implications of the two interpolation-modelling approaches. The aim is to avoid the intensive and time-consuming approach of multiple experimental simulations where possible and to assist researchers in evaluating the relative merits of performance versus quality issues in their own research domain. The integrity of results over time can be explored in this study because the models can be made to predict the date at which each pixel could reach a certain stage in an insect's phenological development. Three metrics are reported that might assist the applied user in determining whether to interpolate model inputs or outputs in a particular study. These include considerations of overall point based 'rms' accuracy, logical errors in the developmental sequence of the insects and the spatial coherence of the interpolated results.

18.2 METHODOLOGY

While many factors influence pest populations (overall numbers), pest phenology (sequence of development) is in contrast relatively well understood. As a first step towards integrated insect/environment modelling incorporating dispersal processes, our goal was therefore to develop a system that can provide predictions of insect *phenology* across space. Such spatial phenologies are in themselves of practical value in two areas. Firstly, they are a useful source of crude measurements of establishment probabilities for non-indigenous pests (Baker, 1994) and secondly pesticide usage may be reduced by timing applications more carefully in relation to insect development. Previous examples of this type of work targeting agricultural or horticultural environments are few, although geospatial methodologies are increasingly being used in pest management systems within forestry settings (e.g. Leibhold *et al.*, 1994). Some American studies have focused on the interpolation of phenologies (e.g. Schaub *et al.*, 1995), but work using spatio-temporal inputs such as outlined in this paper is still unusual.

Insect phenology models (e.g. Baker & Cohen 1985; Morgan 1992) require, at minimum, the provision of sequential daily maximum and minimum temperatures. These variables form the model inputs referred to in this study. Three point process models, originally written to give estimates over time only, were used in order to investigate the consistency of the results. Firstly, a generic phenological model (Baker & Cohen, 1985) has been linked to provide the flexibility required to model non-indigenous species. In this paper European parameters for the Colorado beetle (*Leptinotarsa decemlineata*), which poses a significant threat to British agriculture (Bartlett, 1980), are utilised. It is often the case however that little is known of the biology of an unusual invading species. Accumulated temperatures in Britain relative to those of the suspected country of origin can provide a first means of comparison. For this reason, the UK Meteorological Office model for accumulating temperature (Anon, 1969) also forms part of this discussion. Thirdly, the incorporation of a relatively sophisticated non-linear boxcar model for codling moth (*Cydia pomonella*) (Morgan 1992) reflects the type of model more commonly used for insects indigenous to Britain.

As Figure 18.2 indicates, these three ecological models vary considerably in their conversion of data inputs (daily maximum and minimum temperatures) into pest development rates. At their simplest, development occurs in proportion to temperature accumulation whatever the stage within the pest life cycle the organism has reached. That is, the development rate is time independent. The highest degree of sophistication is represented by the sigmoidal development curves from the model for the development of the codling moth. In this case, development occurs at *pre-assigned non-linear rates* within each stage until reaching a standardised threshold upon which the pest cohort moves to a different stage in its life cycle or expires. Graphically similar, the development of the Colorado beetle moves forward according to *pre-set development thresholds* that determine the development rates per stage.

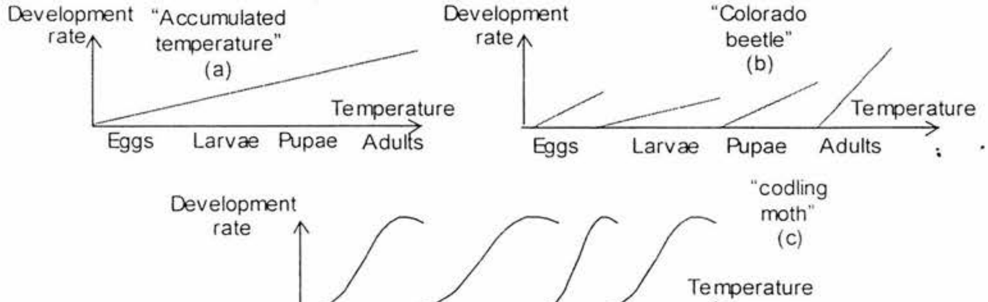

Figure 18.2 Relationships between development rate and temperature within the example phenological models

These process models were originally written to give estimates over time but with only point-based inputs and outputs. They have been adapted to provide predictions over $1 km^2$ neighbourhoods using partial thin plate spline (Hutchinson, 1991) and simple conventional voronoi interpolation methods. The system used to undertake this modelling is a prototype being developed by the authors for Central Science Laboratory (MAFF) for the purpose of undertaking spatial pest risk assessments. At present, the system is a loosely coupled suite of modules incorporating phenological models, interpolation routines, software for pre-processing UK Meteorological Office data files and the export of results in common GIS map formats. A graphical user interface, providing results in ArcView map/chart windows has recently been added to enhance its ease of use for more routine enquires.

So that we might compare the effect of the order of the modelling and the interpolation steps upon the results, splining has been applied either to the input data prior to modelling, or to the results from modelling at data points. The former procedure is considerably more computationally intensive, since both the number of interpolations and number of model runs are increased. For each of the three models, a sequence of daily maximum and minimum temperature inputs throughout the growing season is required as input. Each model run is initiated at the start of a calendar year with a population of viable, mature adults. The process by which interpolator and covariates were selected for the interpolation of daily temperatures is reported elsewhere (Jarvis, 1998).

Given the scarcity of point temperature data relative to the spatial area interpolated, error estimation for the spatial models is carried out using a 'drop out' cross validation methodology (Efron, 1982). This iteratively drops one point out of the interpolation and uses this to estimate the error in the interpolation process. Computation of this measure within the software developed is efficient relative to many mainstream GIS since the process of estimating interpolation functions is separated from the grid production itself. This cross validation facility was used to generate a variety of error metrics from the results from each pest model by means of interpolating inputs (temperatures) and secondly by interpolating the outputs from the phenological model (Julian dates). These are discussed individually below.

18.2.1 Overall root mean square error

In addition to tracking and reporting cumulated error at test locations at the end of the run period, the simulations were also stopped at every development stage within the life cycle to record the accumulation of error over time. Root means square (r.m.s.) errors were computed for each. In the case of the accumulated temperature model, runs were made over different base temperatures over time and the model results are presented as the temperature in °C accumulated during the run period. For insect phenologies, the errors are reported as Julian dates at which particular points in the insect lifecycle are reached. The 'drop out' methodology was used both for interpolated phenologies and temperatures; in the case of the latter, estimates of phenology were made at case points, using interpolated temperature data from which the point in question had similarly been withheld during the interpolation process.

18.2.2 Logical error in insect development sequence

Consideration of logical errors is more commonly made when checking categorical data or database integrity than modelling processes (e.g. Lanter and Veregin, 1992). However, given the necessity to be able to follow the progression of insect development day-by-day at critical times of the year, the question as to whether the correct biological sequence is preserved during a model run is as important as knowing how accurate are the overall predictions for when the insect is expected to reach a certain stage of development. The issue only arises in relation to the estimation of phenological dates (model outputs). We can be sure that, if we run the interpolations of temperature and then run the biological model at each and every pixel, the model enforces the correct sequence; these temporal inconsistencies are not possible if modelling after interpolating.

In the time domain therefore, statistics identifying the logical consistency between the dates at which each defined threshold was reached were computed on the basis of the point cross validation results from interpolated phenologies. Logical errors within the sequence of interpolated phenological output grids at different stages were also mapped for a small study area to investigate the spatial pattern of the phenomenon.

18.2.3 Spatial coherence of the interpolated results

The results were also analysed to investigate how the spatial smoothness or fragmentation of the interpolated results (spatial coherence) reflected those of the original test cases using measures of semi-variance. Experimental variograms for both the estimates of accumulated temperature and Julian dates at the withheld points for the two interpolation-modelling approaches, together with 'actual' results computed using the known sample data, were constructed. The unit of lag used for computation was 20km, 18km being the average nearest neighbour distance between the original meteorological data sites. A measure of the adequacy of the results in terms of their spatial-autocorrelation can be determined on the basis of how closely the interpolated methodologies match those modelled using the known data. Where the interpolation-modelling technique over-smoothes the model results, the variogram range of the modelled data might be expected to exceed that of the actual data, and vice versa. In the worst possible case no range will be detected in the interpolated results but is clearly distinguishable in the 'actual' variogram, implying that simple averaging techniques might perform as well as more sophisticated interpolation algorithms.

18.3 RESULTS

18.3.1 Overall root mean square error

Intuition tells us that errors associated with uncertain daily input values will accumulate through a model run. That cross-validated errors decrease as base temperature rises in the case of accumulated temperature (Figure 18.3) is therefore, unsurprising, since the number of days the base temperature is exceeded and therefore that input errors are propagated will be fewer. The non-linear propagation of such errors in accumulated temperature is indicated by the sharp rise in error using the less accurate voronoi method of interpolating maximum and minimum temperature, as opposed to partial thin plate splines. From this we might infer that even small differences in accuracy gained when interpolating inputs are worth striving for, if this is our goal. In this case, considerable care has been taken with the selection of covariates to guide the splining process, with an annual average

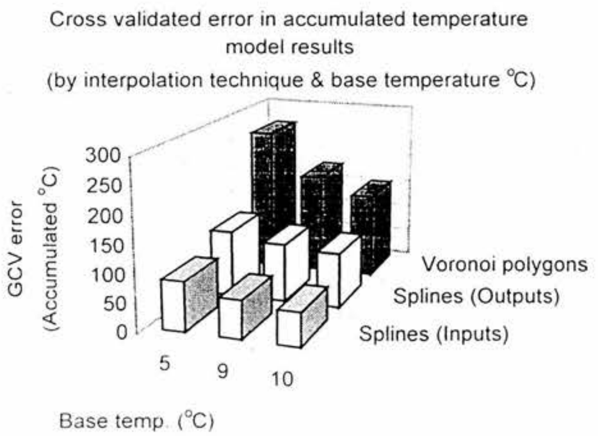

Figure 18.3

error in daily maximum temperature of 0.79°C degrees and of 1.14°C for daily minima. In relative terms however, for accumulated temperature (Figure 18.3), codling moth (Figure 18.4) and Colorado beetle (not pictured) the difference in terms of the GCV point based measure of accuracy at the withheld points between the two interpolation-modelling approaches is slight. For accumulated temperature (°C) this difference is approximately 30°C per annum for each base temperature modelled, while in terms of the date at which the phenological stages are estimated to be reached in the case of codling moth it averages three days. Current applied entomological practice for interpolating temperatures in simple entomological models is to apply voronoi polygons around meteorological sites. The accuracy of results using this method is shown in Figures 18.3 and 18.4 for reference.

Turning to the results for codling moth (Figure 18.4) the effect of the time-dependent model structure causes the spatial error as represented by the cross validation statistics, especially during stage 2 (larval), to fall over time. To interpret this graph, reference to Figure 18.2 is needed. Since the rate of development of the larval stage is slower than that of adults or eggs, the chances of predicting a particular stage of emergence correctly within this stage on any one day are correspondingly high. The overall benefit of interpolating phenologies relative to interpolating temperatures may seem slim from this r.m.s. point accuracy perspective in comparison to choice of interpolator. On the basis of these point statistics alone therefore, the decision to interpolate model inputs or outputs will depend on the operational significance of the error bands and the variance of the individual point error values. In the context of this subject area, where the efficacy of a chemical or biological application deteriorates rapidly then even small differences may be important.

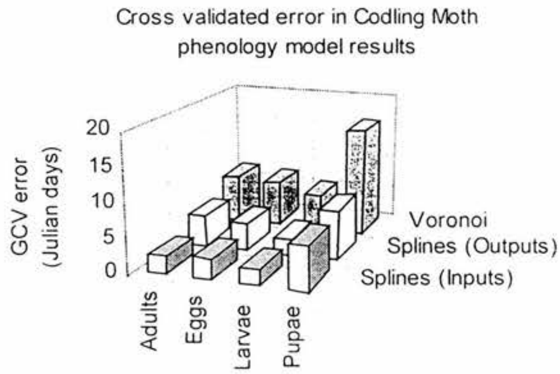

Figure 18.4

18.3.2 Logical errors in time sequencing

Nationally, the proportion of landscape adversely affected by this sequential error is surprisingly high. On the basis of cross validation statistics for Colorado beetle at any one location, the larval stage was found to predate that of the egg stage in 13% of cases with pupae predating larvae in 22% of cases. Overall, one might infer that up to 24% of the England & Wales study area is affected by such errors, the results for each stage not necessarily coinciding. In the case of codling moth, up to half of all test locations show a tendency to support the unlikely biological hypothesis that eggs are laid before adults emerge from over-wintering.

The spatial locations of these erroneous sequences are mapped for the codling moth and Colorado beetle for 100km^2 in the Vale of York area (Figure 18.5). This indicates a strong tendency for errors in the logical sequence over time to occur at relatively high altitudes, where by the nature of the underlying distribution of UK meteorological sites interpolations are relatively poorly estimated. These areas are also ones where environmental gradients, for example of temperatures, are altering rapidly over short distances.

18.3.3 Spatial coherence of interpolated results

In addition to the way in which temporal sequences are represented by the two interpolation-modelling methodologies, the spatial correlation within the interpolated grids relative to the original data provides a further measure of the quality of the results. In the case of codling moth (not illustrated), variograms for actual and the two interpolated methodologies were similar at all stages of development, reflecting the adequacy of both interpolation approaches.

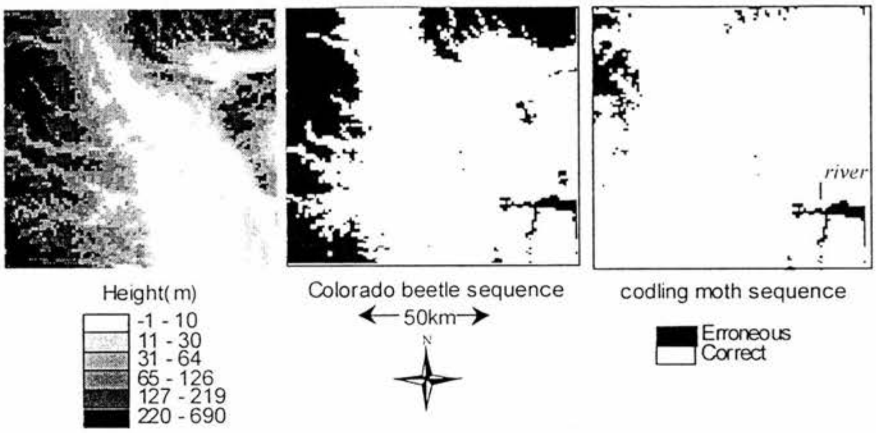

Figure 18.5 Errors in biological sequence created by interpolating phenological results, Vale of York, 1976

Experimental semi-variograms for the Colorado beetle reflected the greatest degree of spatial variability through time as the biological sequence progresses. At the early larval stage, little difference between techniques is seen (Figure 18.6(a)); either the interpolation of model inputs (temperature) or outputs (phenology) is warranted on this basis. However, beyond the pupal stage (e.g. immature adults, Figure 18.6(b)), the results created using interpolated phenologies suggest that spatial association occurs at distances of up to 140km. In contrast, those calculated using known inputs (temperatures

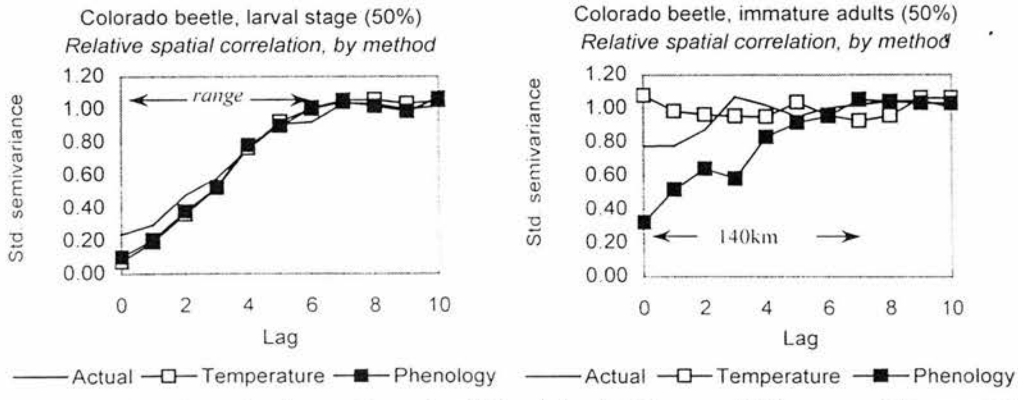

Figure 18.6: Experimental variograms for results of Colorado beetle (a) larvae and (b) immature adults computed using cross validated results from the two interpolation-modelling procedures in comparison with model runs made using 'actual' data

at meteorological sites) suggest that little spatial auto-correlation is discernible. This implies that, if present, spatial association will be highly localised to within 20km or under. Surfaces for immature adults of the Colorado beetle created by interpolating the model outputs (phenological dates) will appear grossly over-smoothed in comparison. The latter interpolation technique provides a false visual impression. Variograms computed using 'actual' data for each development stage in turn (Figure 18.7) demonstrate an expected fragmentation of the phenological surface as the growing season progresses. This arises since the underlying distribution of weather patterns is inconsistent between localities on a day to day basis.

As for Colorado beetle, interpolating input temperatures for a 5°C base threshold model reflects better the 'actual' accumulated temperature surface as shown in the experimental variograms of Figure 18.8, but the overall degree of fragmentation

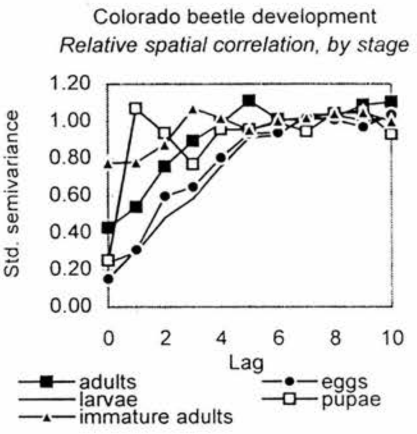

Figure 18.7

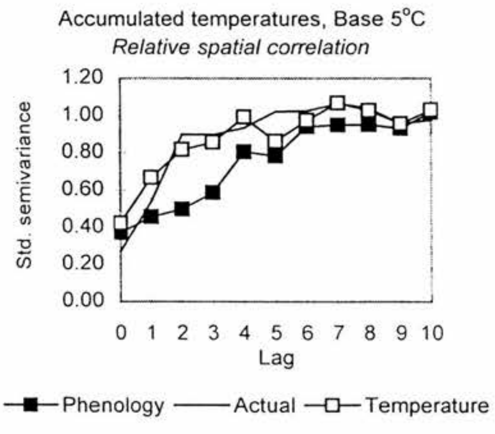

Figure 18.8

represented relative to the results for the Colorado beetle model is considerably lower.

Over short model runs, interpolating model outputs appears to perform adequately. However, as time progresses the variance within the phenological Julian date and accumulated surfaces increases. At a model dependent point, interpolating model outputs may become inappropriate in comparison to interpolating inputs, the spatial autocorrelation of which will stay relatively constant and measurable throughout the season in the case of daily maximum and minimum temperatures.

18.4 DISCUSSION

Numerical analysis of the model surfaces created by interpolating temperatures and phenologies confirms the importance of considering carefully whether to interpolate model inputs or outputs. Despite the similar overall r.m.s. point accuracy of results obtained by modelling inputs and outputs, problems may arise regarding the logical sequence of output grids over time. For the modeller requiring a single output this is unlikely to present a difficulty, while for those needing a sequence of outputs for further modelling such errors may be critical. The relevance of this error measure to the particular ecosystem under investigation may be gauged by mapping the phenological results, although it should be noted that this provides a relative, rather than absolute, measure of error. Additionally, levels of spatial fragmentation in the Colorado beetle results (Figure 18.6(b)) indicate that for long model runs using a model containing abrupt coherence of the model results. Even where the semi-variogram analysis and overall point accuracy results between modelling inputs and outputs are similar, variance statistics show the interpolation of inputs rather than outputs to mimic more closely the underlying data. Using all three metrics together, rather than the more traditional use of the aggregate r.m.s. measure alone, provides a more rounded view of the spatio-temporal ramifications of the question posed.

The overall wisdom of considering the interpolation of model inputs rather than model outputs may also be considered in the light of this practical experience. In this case study, a number of factors pointed to the use of interpolated inputs, and at minimum a comparison of techniques. Firstly, the longer-term aim of the entomological system under development is as a tool within a dynamic, integrated modelling environment. Predator, prey and crop models alike require the input of temperature amongst other variables. Furthermore the modelling of dispersion will involve multiple sequential surfaces, whichever interpolation technique is chosen. In the latter case, increases in computational intensity as a result of interpolating model inputs rather than outputs will relate to added model runs only, rather than both added model runs and interpolations.

Table 18.1

	Interpolate inputs	Interpolate outputs
Limited computing power (PC environment)?		✓✓
Single output grid required?		✓✓
Smooth model results expected?		✓✓
Obvious gridded variables to guide model results?		✓✓
Single input type?		✓
Input variables known to be difficult to interpolate accurately?		✓✓
Model results easy to validate?		✓✓
Implementation to be within a GIS?		✓✓
Input variables perceived to be spatially 'smooth' relative to model outputs?	✓	
Multiple input types with sample networks of different densities?	✓✓	
Desire for further integrated modelling using similar inputs in future?	✓✓	
Multiple sequential outputs?	✓✓	
Model outputs difficult to verify?	✓✓	
Interpolated inputs of value in their own right?	✓✓	
Zero values in some output surfaces anticipated?	✓	
Lack of physical justification for guiding variables of model results?	✓	
Multiple input variables process guided by different variables?	✓	
Complex linked model with abrupt thresholds?	✓	

✓✓ - Recommended

✓ - Likely indication of 'best' practice

Additionally, input data networks for other input variables required in the future, such as rainfall, do not necessarily coincide with those for temperature. To constrain modelling to points where all inputs are collected would reduce sampling densities to inappropriate levels. As a more intellectual issue, where the interpolation of model results are concerned, the basis for selecting suitable variables to guide the interpolation process is much weaker (Grayson *et al.*, 1993), especially where the model is non-linear or contains multiple thresholds. Finally, validating model output surfaces in the case of non-indigenous pests such as the Colorado beetle is impractical, whereas both input grids and the biological model can be independently tested.

The practical problems of spatio-temporal modelling within proprietary GIS favour the interpolation of model outputs (e.g. Johnston *et al.*, 1996). It may for example prove difficult to link the software with the high level code of the point process models, or to handle temporal sequences of interpolated data as anything but complete landscape grids. Obtaining simple 'drop point' cross validations is likewise problematical, while macro languages are computationally inefficient. The range of interpolation methods available within proprietary GIS software may not meet the needs of the sophisticated environmental modeller, whether it is one intending to interpolate either model inputs or outputs. In this case it may be that interpolation will be by public domain or in house code, as here. Then the barriers to interpolating model inputs rather than outputs relate more to computing power than structural constraints. Our experiments indicate an approximate thirty-fold increase in computing time between interpolating model outputs versus interpolating input grids and then modelling. These issues are summarised within Table 18.1 above as a question set that could be applied in other ecological contexts.

18.5 CONCLUSIONS

Within an entomological setting, analysing the propagation of spatial and temporal errors in model predictions charts a new research area. Previous studies have interpolated results from phenological models unquestioningly, without incorporating checks on the spatial and temporal integrity of the process. The example of modelling the development of the Colorado beetle based on daily synoptic weather conditions shows that the common practice of interpolating the results of an at-a-point model will not *necessarily* produce results that are spatially and temporally coherent, even if point-based accuracy statistics (such as r.m.s.) seem satisfactory. In particular, logical inconsistencies in biological sequence may arise when interpolating phenologies that are avoided when interpolating inputs prior to running the phenological models. The interpolation of model inputs is also particularly beneficial for modelling the later stages of insect development, where spatial association between phenological results may be highly localised in comparison to that of the daily temperature input data.

Practical investigation of the question 'should we be interpolating inputs or outputs?' in relation to insect phenologies has resulted in a generic set of considerations that could be asked as part of the modelling process. These relate to issues of computing environment, model complexity and further use of the results. Considering such a question set does not require a large investment on the part of the modeller, who may be reluctant to delve initially into multiple simulations to solve the problem without necessarily seeing any direct benefits. There may however be no clear answer, and a number of focused simulations are recommended in such cases. This study demonstrates the value of three metrics designed for this purpose:

- Comparison of root mean square accuracies between interpolation methodologies at known points;
- Checks for logical consistency between temporal outputs;
- Analysis of relative semi-variance in results between models run using actual input data, interpolated input series and interpolated outputs.

More generally, the work highlights the need for further research to combine spatial and temporal error propagation methods and the need to understand the spatial significance of attribute error. Principles used to determine the integrity of spatial databases using logical rules may also be applied to spatio-temporal modelling procedures. The mathematical results for the particular phenological models exemplified are application specific. Nevertheless, the issues considered are generic to many other environmental models using time-varying inputs.

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The production of spatial weather data for the purpose of predicting crop pest phenologies

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THE PRODUCTION OF SPATIAL WEATHER DATA FOR THE PURPOSE OF PREDICTING CROP PEST PHENOLOGIES

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Abstract

Annual sequences of daily minimum and maximum temperatures have been interpolated to $1km^2$ spatial resolution throughout England and Wales using partial thin plate splines, de-trended inverse distance weighting and quadratic trend surface analysis. Commercial interpolation packages and GIS were unable to meet the levels of inter-operability required to link these results with phenological models: individually tailored software was therefore developed. Data was de-trended according to knowledge of the principal climatic processes operating. Results suggest partial thin plate splines perform with accuracies comparable with the best of those in the recent literature. Average accuracies by cross validation for maximum and minimum temperatures achieved 0.79°C and 1.15°C respectively, the figure for winter minima 0.97°C. Surfaces on days with blocking anticyclones are those most difficult to predict. It is suggested that an iterative process when interpolating which explores the balance between reliance on spatial auto-correlation and physical modelling may ultimately lead to a relatively parsimonious model.

INTRODUCTION

Phenological models are increasingly being used to enhance pest assessment and control strategies. Such simulations are critically dependent on daily temperature data since insects are poikilotherms. However, commonly available daily weather data is of a point nature, so most phenological simulations to date have likewise been restricted. This paper focuses on the production of weather data as input to a prototype spatial pest prediction system for England and Wales.

INTERPOLATION OF DAILY MAXIMUM & MINIMUM TEMPERATURES

Work exploring the interpolation of daily maximum and minimum temperatures falls broadly into two main camps: where interpolations form one element of a linked model used for practical purposes, well tried inverse distance weighting or local averaging techniques appear to be 'de-facto' (e.g. Van der Goot, this volume). In contrast, where the focus has been upon the interpolation of single surfaces, a greater variety of techniques have been explored (e.g. Collins & Bolstad 1996, Laughlin et al 1993, Cornford 1996).

Two broad message come from these different tranches of literature. The first is that in purely pragmatic terms, simple techniques such inverse distance weighted interpolations and trend surfaces to a lesser degree can provide reasonable if not optimum accuracies. Spatial auto-correlation compensates for paucity of model, subject to data configuration. Secondly while external data to guide or de-trend interpolation can be of great value where data are sparse, they should be chosen with regard to underlying process (Grayson, 1993). It is interesting to note in this context that previous proponents of physical models for determining minimum temperatures (e.g. Laughlin & Kalma 1987) have themselves turned to interpolation to improve their results (e.g. Laughlin et al, 1993). This leads to the suggestion that a balance between the two approaches might provide a practical advantage. This can be achieved by placing a stronger reliance on auto-correlation than those who focus strongly on de-trending data prior to interpolation (e.g. Cornford, 1996) but nevertheless ensuring a rigorous compatibility with physical process in selecting the primary guiding variables. Given the constraints of working within a tightly coupled system, critical factors that must be retained include mathematical accuracy, automatic parameter selection and the building of software that allows inter-operability between the interpolation procedure and process model.

METHODOLOGY

Analysis fell within two distinct phases. The first reflects the need identified by Grayson (1993) to consider underlying processes affecting the data being interpolated, and draws heavily in approach on recent work by Cornford (1996) in conjunction with older British topo-climatic research (e.g. Tabony 1985, Manley 1944). Although they worked with monthly data, the methodology of Lennon & Turner (1995) for Great Britain has nevertheless been a strong influence on the approach taken. This literature points to the importance of the sea, height, latitude and urban development as primary variables to guide the interpolation of temperatures in a British context. Our strategy also includes more detailed topo-climatic modelling, but will focus in this respect solely on climatic conditions where interpolation accuracy proves poor in a post-hoc iterative cycle. Owing to the high degrees of inter-correlation anticipated between potential primary variables, reliance on standard software for automatically extracting 'best' subsets was avoided. Variables were instead chosen with regard to both tolerance and contribution to variance.

In the second phase of analysis, maximum and minimum temperatures were interpolated having been de-trended using the principal guiding variables determined by regression analysis. Inverse distance weighting (IDW), partial thin plate splines and quadratic trend surfaces were explored, these techniques chosen in reflection of their common usage for climatic interpolations at a variety of spatial and temporal scales. Software was coded in FORTRAN 77 in conjunction with modules from ANUSPLIN (Hutchinson 1991) to meet this goal. IDW power parameters were selected using cross validation. Many proponents of kriging advise strongly against the automatic fitting of variograms (e.g. Deutsch & Journel 1992), making this technique less appropriate where multiple surfaces as required. Additionally, the number of data used (166 stations for England and Wales) was arguably too sparse for variogram modelling.

RESULTS

The initial topo-climatic modelling using linear regression suggested height, the percentage of land as opposed to sea within a local 50km^2 grid, log northing and a specially created urban index as the primary landscape factors influencing temperatures. Reliance on linear regression was found to be a considerable disadvantage when considering variables such as distance from the sea.

The results of interpolating the data, de-trended by the four selected primary variables, prior to further analysis, are illustrated within Figure 1 below.

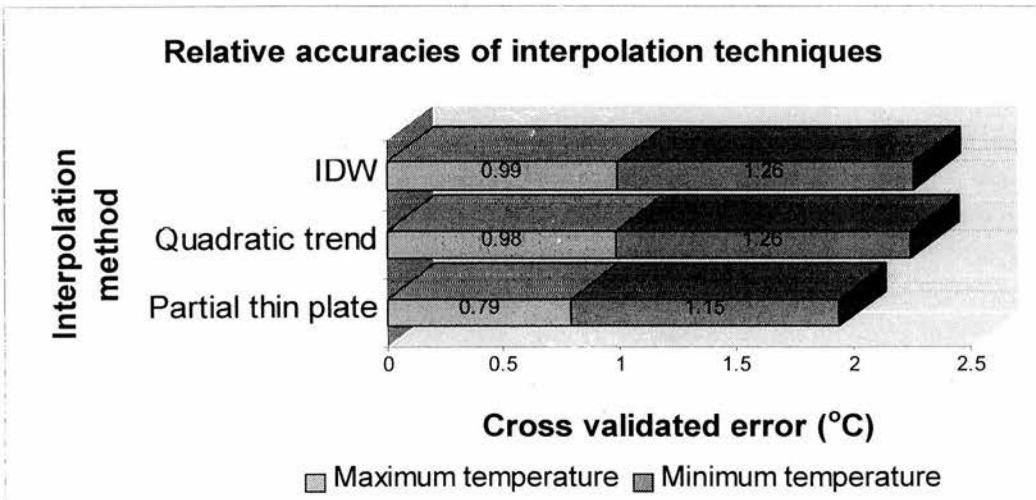

Figure 1

As expected, accuracies for maximum temperatures proved higher than those for minima. Suprising however is the poor performance of inverse distance weighted interpolation relative to that of the enhanced quadratic trend surface. Differences between techniques are slim, but the effect of small errors is an accumulative one within the coupled phenological models: subsequent phenological results have shown even slight improvements in temperature to have significant effects. Despite their higher computational intensity therefore, partial thin plate splines have been chosen as the technique of choice for further exploration.

Figure 2 below illustrates the accuracies for maximum and minimum daily temperatures achieved by the best model, partial thin plate splines, throughout the annual cycle. Average accuracies, computed by cross validation were 0.79°C and 1.15°C respectively, the figure for winter minima was lower at 0.97°C. While direct comparisons with other work using different data sets are not appropriate, they are in the same order as those achieved in other recent studies for Britain (e.g. Cornford 1996).

These accuracy results were analysed further in relation to the Lamb classification for each day in order to identify whether any relationship was apparent between interpolator performance and prevailing weather type. Analysis showed that for minimum temperatures, 47% of errors above two standard deviations from the mean (>2.0°C) relate to weather type 0 (blocking anticyclone). This is confirmed by visual inspection of Figure 2, on which type 0 days form a backdrop to the cross validation results. This in part relates to the unusually strong influence of high pressure systems over Britain in 1976, but the same relationship was also found strongly significant when analysed by proportion of occurrence.

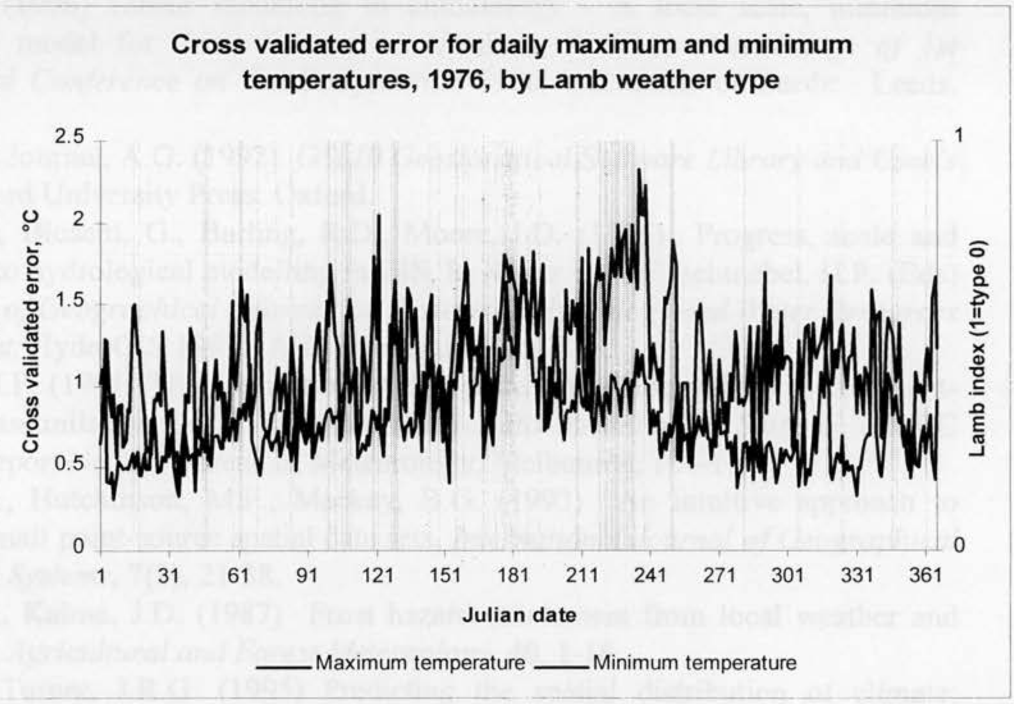

Figure 2

CONCLUSIONS

This study shows that, even working within a tightly coupled environmental modelling framework, more advanced interpolators such as partial thin plate splines may be utilised to good effect. In a mathematical sense partial thin plate splines align with the more computationally intensive co-kriging methodology, and with more data this technique may prove worthy of comparison also. While studies that focus on physical processes have intellectual merit, there nevertheless seems to be a pragmatic payoff in accuracy terms between reliance on spatial auto-correlation and detailed modelling prior to interpolation. Further topo-climatic analysis will therefore focus on modelling variables associated with high pressure conditions, especially those of the summer months when insect development is at its fastest and errors thus most significant in phenological terms. Close attention will also be paid to the landscape characteristics

Presentations

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